DOCTOR OF PHILOSOPHY

Development of Agent-Based Heuristic Optimisation System for Complex OEM Flow-Shop under Customer-Imposed Production Disruptions

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Development of Agent-Based Heuristic Optimisation System for Complex OEM Flow-Shop under Customer-Imposed Production Disruptions

By

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Abstract

Original Equipment Manufacturers (OEMs) flow-shop systems are exposed to production disruptions caused by automotive assembly customers. When the customer assembly line experiences uncertainties, demand requirements change. Therefore, the problem extends to affect the OEMs flow-shop production planning and scheduling. The continuous customer changing demand requirements in terms of quantity, sequence and time of delivery of orders create disruptions. The combination of these types of disruptions on OEM flow-shop makes the problem complex to solve, hereby requiring a more robust approach, especially in an environment where customers' demand satisfaction is prioritised, despite disruptions.

In this research, a new and innovative disruption-resolution framework is proposed to tackle customer-imposed disruptions in OEMs flow-shop. The framework integrates the dynamics of agent-based simulation, inventory control, and adaptive heuristic algorithm. The heuristic algorithm is proposed to specifically help OEM flow-shop adapt and accommodate disruptions through an innovative inventory 'borrow and replenishment' strategy for production support when disruptions occur. The autonomous capability of agent-based simulation was adopted for simulating the actions and interactions of flow-shop resources (agents) for better system assessment of the system. As production resource such as operators and machine play a vital role in performance improvement, agent-based method is adopted to simulate system resources interaction, to improve productivity further

Based on combination of disruptions occurrences, the research conducted different scenario experiments using real-life data to verify and validate the proposed approach. The results of the proposed approach, in terms of selected Key Performance Indicators (KPIs) showed an improved performance of resources by 6.89%, which led to increased number of orders satisfaction, reduced number of late/unsatisfied orders by 8.28% improvement, compared to both a sequential replenishment approach and the current flow-shop operation ("As-Is"). This showed the effectiveness of the proposed framework approach to solving the OEMs flow-shop customer-imposed disruptions problem of this nature.

Dedication

This thesis is dedicated to my boys: Alexander and Jason. To my wife: Motunrayo. You guys are my motivation for success.

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There is no research study ever completed with one person's efforts, certainly not this one! The dream of completing a PhD degree became a reality through the grace of God. God is the one who sent help my way from start to finish. However, certain individuals made it worthwhile.

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To my siblings, you guys are the best I could ever ask for and I want to keep having you as siblings over and over again if I can come this world multiple times.

Finally, certainly not the least. To my loving wife, how would I have done it without you? I remember every single support and I love you forever. Alexander and Jason, you are my strength...thanks for walking through this journey with me.

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1. Adediran, T.V. and Al-Bazi, A., (2017) Agent Based Model for Complex Flow-Shop Manufacturing Systems with Customer-Related Production Disruptions. *In Information Technology (ICIT), 17-18 May 2017 8th International Conference* (767-773), *Amman Jordan*. IEEE.

2. Adediran, T. V, & Al-Bazi, A. (2018) 'Developing Agent-Based Heuristic Optimisation System for Complex Flow-Shops with Customer-Imposed Production Disruptions'. *Journal of Information and Communication Technology*, 18(2), 291-322 http://www.jict.uum.edu.my/images/vol17no2apr18/ms291-322.pdf

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1. An Agent-Based Heuristic Approach for Solving Complex OEM Flow-Shop Productions under Customer Disruptions. **Computer and Industrial Engineering Journal**

Chapter 1: Introduction

1.1 Introduction

This section presents the introductory part of the thesis, which includes the background, and the motivation for this research. It includes the classification of scheduling problems where the flow-shop falls. In addition, the research aim and objectives are highlighted in this section. The brief overview of the problem definition is presented, while the research tools and techniques, deliverables and the benefits to industry as well as academia are discussed. The chapter concludes with the structure of the entire thesis.

1.2 Background

In today's era of global market competition, product quantities, sequences and time to market form part of the challenging factors, which manufacturers try to deal with daily (Mulky 2013). The increasing changes in demand requirements of manufacturing products and volatility of their supply chain network have become overwhelming for production decision makers (Christopher and Holweg 2011), for Original Equipment Manufacturers (OEMs) of automobile parts and components, where production relies on customer demands, satisfying these demands requirements becomes a priority to remain in business. In this context, the OEMs are part of car manufacturing supply chain network that processes or/and assembles raw materials. They supply other semi-finished products as parts and components for the assembly line of the main automobile manufacturing customers. Thus, OEMs seek to explore measures and adopt strategies to respond to their customer-changing environment causing disruptions (Kleindorfer and Saad 2005) in form of demand quantities, delivery due time and sequence.

The nature of disruptions in the OEMs has made the use of traditional production planning and scheduling packages decision-making impractical. This is because existing techniques are no longer suitable for this type of emerging disruption problems. Thus, a more adaptive approach is required. For this reason, the embedded agent-based technique is explored in this study to achieve adaptive approach, which facilitates timely delivery and exact quantities of customer demand requirement despite disruptions. Agent-based technique is useful as regards to the nature of the emerging disruption problem in this study. The details of agent-based applicability in this study are documented in Fung and Chen (2005), Wojtusiak *et al*. (2012), Monostori *et al*. (2006), Sekala and Dobrzanska-Danikiewicz (2015), Shen *et al*. (2006), Gomez-Cruz *et al*. (2017), Kleindorfer and Saad (2005). The problem of disruption in OEM industry discussed in this study is associated with customer demand, order sequence, quantity and delivery due time, and are classified under production disruption (Paul *et al.* 2015).

The inventory and its replenishment concept have often been linked with production in manufacturing industry. It is an important contributor in manufacturing production as it relates to raw materials, work-in-progress, and finished products storage (Luikkonen 2015), as discussed in related supply chain problems in Wang *et al*. (2015), William and Tokar (2008), Hammami *et al*. (2017), Kleindorfer and Saad (2005). Therefore, the inventory replenishment concept is associated with disruption problems in OEMs as ‘strategic’ production support to facilitate the effectiveness of the proposed approach.

The performance of the OEMs in manufacturing sector is vital, as it can influence business revenue, which measures profitability. For these reasons, this study appeals to manufacturing stakeholders, researchers, government agencies and public with direct interest in the OEMs manufacturing performance.

1.3 Research Motivation

The motivation for the research is kindled by the awareness of the challenges faced by Original Equipment Manufacturers (OEMs) industry, where customers strongly influence production activities through persistent changing requirements. This type of business relation increasingly adds pressure on production processes. This has damaging effects such as overstretching capabilities, low utilisation and production shortages. The researcher is therefore motivated to develop a sophisticated approach that accommodates this problem. The approach is proposed as an adaptive means of resolving production problems and subsequently satisfying customer changing demand requirements. The research outcome would be helpful as valuable contribution to the existing knowledge. The research problem and techniques can inspire other researchers to propose better approaches that deal with emerging problems in similar domain.

1.4 Classification of Scheduling Problem in Manufacturing Systems.

Many different classifications of scheduling problems have been addressed for manufacturing production under uncertainty (Lin et al. 2012; Li and Ierapetritou, 2008; Rasconi, et al. 2010, Sotskov, 2013). The classification of Hagar et al. (1995) is one of the most popular. The classification considered scheduling problems under factors such as: the method of solving problem and performance measures of schedule, the number of machines involved, and the nature of problem. The problem nature divides scheduling process into two types; uncertain and deterministic scheduling as shown in Figure 1.1. The uncertain scheduling comprises of fuzzy and stochastic scheduling, while the deterministic scheduling are made up of the two major classes; single machine and multiple machine scheduling problems. The multiple machine scheduling focuses on the problems affecting parallel machines, flow-shop, and job-shop environments.

Figure 1.1 Scheduling problem classifications (Hagar et al. 1995)

In the study, the scheduling problem of disruption falls under the flow-shop multiple machine production environment, which is deterministic in nature. Therefore, it is important to understand the meaning of flow-shop scheduling problem from the current research perspective.

Although there is no accurate definition that can be pinned down to flow-shop scheduling problem, different researchers' perceptions are considered. Dudek et al. (1992), referred to the perception of Baker (1974), who defined flow-shop scheduling as a situation where orders (jobs) are processed on *m* stage sequentially, where *m* referred to machine at each stage. In another viewpoint, Johnson in 1954 defined flow-shop scheduling problem of a case of a two-machines and *n*-jobs to be processed.

In the current research perspective, the flow-shop scheduling problem is associated with a group of machines in parallel and arranged in a number of series stages. In this kind of machine arrangement, there are number of parallel and identical machines at each stage. It is setting where at least one job can be processed by each machine whereas each job can skip one or more machine process stages.

1.5 Research Problem-Production Disruptions in the OEMs Environment.

The research problem description has been deployed from challenges facing OEMs manufacturing flow-shop operation. It is particularly related to OEMs flow-shop facility of automotive parts and components production. It is a setting where automotive parts and components (order demands) are requested by customers (automotive assembly line) from their supplier (OEMs facility). In a typical scenario, customer orders are requested in a specific quantity, sequence and time of delivery. These initial customers' order request changes in requirements on assembly line due to uncertainties. The uncertainties result in the case of order being cancelled, sequence being altered and delivery due time being updated. As a consequence, an order cancellation increases the idle time of machines and operators. Change in the sequence increases the number of machine setups. Change in delivery due time causes high number of late or unsatisfied orders. These changes affect OEMs flow-shop entirely and cause low utilisation. Low resource utilisation causes low productivity and production shortages. As the OEMs facility seeks to and is committed to customer satisfaction despite disruption, resolution action is paramount. For this reason, resolution measure is required to help adapt to and accommodate inevitable disruptions with the minimum impact of OEMs flow-shop production.

1.6 Research Aim and Objectives

The aim of this research is to develop an adaptive framework for production rescheduling in OEMs flow-shop industry under disruption problems caused by changing customer requirements. When there are disruptions, the OEMs system needs to adapt to changes and accommodate the impacts on production processes to the minimum while satisfying customer demand. In order to achieve the above aim effectively the following objectives have been considered:

1. To review preceding studies in the area of flow-shop production system and the disruption problems along with various tools and techniques used to solve these problems. This includes related studies in the areas of supply chain, manufacturing, production and scheduling.
2. To identify logic of the flow-shop operations and other related entities.
3. To model and study the behaviour of flow-shop in response to the disruption problems.
4. To develop an adaptive heuristic algorithm capable of responding to and accommodating customer-imposed production disruptions.
5. To integrate the developed heuristic algorithm and inventory support to be embedded in the simulation model for a better flow-shop production performance.
6. To collect data from real-world problem required to model the flow-shop system and experiment the disruption effects on production processes. This includes identifiable constraints associated with product planning, and scheduling.
7. To conduct experiments for production disruption under different scenarios and analyse the flow-shop production behaviour compared with "As-Is" and other approaches.
8. To verify and validate the developed models to ensure accuracy and effectiveness.

1.7 Research Tools and Techniques

The way in which research is carried out is thought to be very crucial aspect of the research project. Likewise, the research data in this project is considered a mandatory input to create a simulation model. However, tools and techniques serve as baseline for such data to be executed. Hence, the following research techniques were explored and considered:

- A literature review of previously faced problems in production planning and scheduling settings and approaches used in tackling them.
- A number of selected logical techniques such as Use Case diagram, process mapping, flowcharts and activity cycle diagrams were used to identify logic for effective design, implementation, analysis and adequate understanding of the problem requirements.
- A selection of methods including onsite visits, observations and interviews approach were utilised to capture details and required data to develop the proposed approach.

- Agent-Based Modelling is adopted as an autonomous simulation methodology to develop simulation-based production planning and scheduling model.
- Adaptive solution algorithms is developed and proposed to respond to the research problem for efficient solution realisation.
- Excel VBA programming embedded within MS Excel is utilised to model the agent-based simulation entities and environment.
- A case study approach is adopted to verify and validate the developed simulation model output and to compare it with a real-life situation.

1.8 Research Deliverables

Achieving the project deliverables is considered particularly important as it helps in determining the success of the project and check if the project is worthwhile. The following are the research deliverables obtained.

- A comprehensive review, which analyses previous problems, encountered within flow-shop manufacturing production systems, and tools and techniques used to improve such problems.
- Collection of related logical diagrams including production processes, activity diagrams, UML and flow charts etc.
- A collection of data specifically for OEMs flow-shop production operations.
- Integrated agent-based simulation model, which imitates the flow-shop production.
- An adaptive heuristic algorithm specifically for the disruption problems solution and similar problem background.
- Selected case study description regarding the OEMs operation in real life used to validate and verify the developed model.
- Verified and validated agent system simulated model results and analysis.

1.9 Benefits to Academia

The benefits of this research study to academia are as follows:

- Filling in the gap and contributing to the academic body of existing knowledge through the identified problems and solution approach with the OEMs flow-shop.

- Serving as knowledge base, which provides insights beyond the current work and point of references to related studies.
- Creating new paths for further research to learn more from unexplored but related problem areas to this study.

1.10 Benefits to the OEMs Industry

The benefits of the outcomes of this research to the OEMs industry are in number of ways. The following are some of the significant benefits.

- Helping production managers to make well-informed decisions in readiness for disruptions.
- Helping to minimise late/unsatisfied orders and improving customers demand satisfaction.
- Improving flow-shop productivities in terms of key performance indicators.
- Providing a solution prototype for production problems of similar conditions.
- Driving production growth through better customer relationships through prompt customer services.
- Optimising production resources significantly.
- Simplifying the complex nature of the disruption problem and its consequences.
- Encouraging utilisation of idle time to improve productivity.

1.11 Research Scope

The scope of this research is focused on uncharted combination of disruptions affecting particularly the OEMs flow-shop industry. Specific emphasis is based on the following aspects:

- The impact of disruptions on production and inventory levels
- Customer satisfactory level in terms of order quantities
- The OEMs flow-shop and inventory

Moreover, the disruption that is caused by customer through their assembly line on OEMs flow-shop is targeted.

1.12 Thesis Structure

The structure of this thesis (Figure 1.2) is organised as follows:

- **Chapter 1**: This chapter sets the pace and introduces the research endeavours. It consists of the background of study, problem introduction, research aim and objectives, deliverables, tools and techniques, scope and the benefits of the outcomes in academic and industrial environment.
- **Chapter 2**: It reports the review of literature in the areas of flow-shop, supply chain manufacturing that focuses on production disruption and related problems. It also consists of the review of various methods adopted by researchers in the past. Finally, it presents critiques of selected literature and identifies gap in knowledge.
- **Chapter 3**: The methodology chapter is the documentation of the proposed framework and all approaches implemented in this study. It demonstrates the application of the selected methods for the specified customer-imposed production disruptions in flow-shop system.
- **Chapter 4:** The chapter provides the flow-shop operation specification and modelling interface. In this chapter, system architecture, UML diagrams, data flow processes, screenshots from the developed system is discussed.
- **Chapter 5**: This is the chapter where the detail of Unipart Eberspacher Exhaust Systems (UEES), the OEMs case study company is discussed. It consists of description of the flow-shop operation, product types and the representative flow diagrams. It also contains the method of data collection and the details of data for experiments.
- **Chapter 6**: This chapter presents the experimentation of different scenarios under disruptions. It demonstrates the application of the proposed approach and the comparison with other approach.
- **Chapter 7**: the conclusion and recommendation chapter give summary account of the research lesson learned from different perspectives. It also presents recommendation for future research.

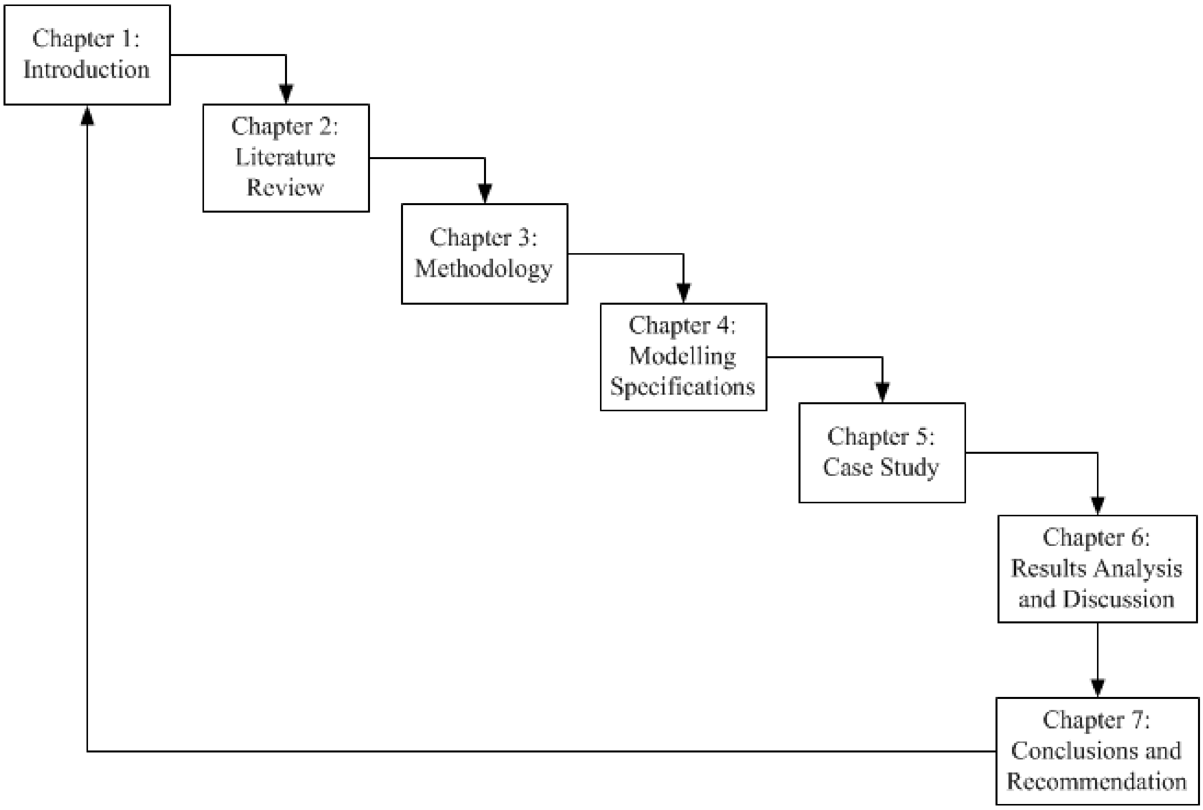


Figure 1-2 Thesis Structure

1.13 Chapter Summary

In this chapter, the research study has been introduced and gives understanding of research background. The next chapter discussed review of relevant literature in the current area of research: production disruption and methods that have been applied in the past.

Chapter 2: Literature Review

2.1 Introduction

Over the years, researchers and experts have become increasingly concerned about problems affecting efficiency and production performance in manufacturing industry. One of these problems are disruptions, which are unplanned occurrences (Craighead et al. 2007) that prevent smooth running of the manufacturing production systems in a random amount of time. In a flow-shop manufacturing setting, which is the focus of this study, disruptions affect production causing delivery delay, poor quality, long lead-times and hence huge cost of production (Rathore 2006). Katragjini et al. (2012), stressed that there are several disruptions capable of affecting production process and invalidate the original schedules. Due to the unpredictable nature of flow-shop manufacturing in terms of disruption, production managers struggle to find stability with production schedules and satisfy customers in the highly competitive business environment.

In this chapter, various disruptions affecting manufacturing systems and related sectors that have direct or indirect impacts on manufacturing are considered. The selected lists of related literature are grouped under two main categories of disruptions called internal and external disruptions. In Cauvin et al. (2009), internal disruption is described as enterprise resources such as material defaults, machine unavailability, decreased performance, operator availability etc. The external disruption is described as customer orders such as delayed delivery date, order cancellation, order change etc.

However, in this review categories, internal disruption refers to events and factors that affect or with potential of affecting production scheduling or process from within the manufacturing or related sectors environment. On the other hand, external disruption refers to those from outside the manufacturing or related sectors environment. Alongside various causes of disruption under the two categories, application and association of different tools and approaches used to tackle disruption problems are also reviewed. Different responses to disruption as well as association of inventory and integration of agent-based simulation related approaches are reviewed. The chapter extends by identifying gap in knowledge which launches the current research to offer its contributions. The chapter concludes with chapter summary.

2.2 Internal Disruptions Affecting Flow-Shop Manufacturing and Related Environments.

In this section, previous studies on various disruptions and causes of disruptions that falls under the internal disruption categories in flow-shop manufacturing and related sectors are presented. The review basically focusses on various disruptions from within the related sectors and how they are been tackled.

The work of Surjandari, et al. (2015) focused on increased rate of product defect at each stage of production causing disruptions. This relates to scheduling problem in an assembly job shop with parallel machines that produce multi-item multi-level product. They developed a batch scheduling model and the objective of the model is to minimise the defect rate as well as total actual flow time (FT). Among the factors considered for the model are the due date fulfilment and assignment in both static and dynamic conditions. The insertion technique was adopted in the scheduling process and heuristic algorithm was used for both static and dynamic conditions. Computational results which validated the proposed algorithm and coded in Java language using Eclipse IDE was used to demonstrate the algorithm performance.

A set of realistic working conditions was the issue in Karimi-Nasab, Modarres, and Seyedhoseini, (2015) investigation. The problem relates to joint lot sizing and scheduling in a job shop environment. They proposed a mathematical model to solve this problem. The main assumption of this model taking into consideration was that of flexible machines that is capable of changing working speeds, which they termed 'process compressibility'. Another important assumption was that of periodical sequences, determined in a way to obey fixed global sequence. The research also considered precedence relationships prioritising needed processes of item type over the corresponding machines. The problem was NP-hard and so solved using Particle Swarm Optimisation (PSO) algorithm. For performance evaluation of the proposed algorithms, LINGO 11.0 was adopted for verification in terms of optimality gap. Demand type is an important factor to consider when considering manufacturing system scheduling because it acts as a driving force for the entire system.

In Lozano and Medaglia (2014), sequence-dependent batch and product incompatibilities was found to be factors causing disruption in an automotive glass facility. The influence of this disrupts job scheduling in a parallel machines environment, causing completion delay. The problem case is based on a complex real-world scheduling existing in the bottleneck workstation of production line of an automotive safety glass manufacturing facility. The objectives of the investigation are to maximise the utilization of the parallel machines and to minimise the delay in the completion date of each job in relation to a required due date which is specific for each job. The following constraints were considered; batch capacity, sequence-dependent processing times, incompatible product families, additional resources and machine capacity. To solve the problem, two phases heuristic approaches were proposed to combine exact methods with search heuristics. The first phase consists of four stage mixed-integer linear program used for building the batches while the second phase is based on Greedy Randomised Adaptive Search Procedure adopted for sequencing the batches assigned to each machine. For experimental purpose, real data of 100 jobs built was considered from manufacturing facility. The result of the experiment revealed positive outcomes in terms of average computing time, and solution quality.

Like Lozano and Medaglia (2014), who considered disruption problem of sequence-dependent batch and product incompatibilities, Yalaoui and Chu (2003) also considered sequence-dependency but for setup times. They investigated a simplified real-life identical parallel machine scheduling with sequence-dependent setup times and job splitting to minimise makespan. To solve this problem, they proposed heuristic solutions which were in two parts. The first part reduced the problem into a single machine scheduling problem with sequence-dependent setup times, which is transformed into a Traveling Salesman Problem (TSP) and solved using Little's method. The second part was done by obtaining the results from the first part, which was then improved in a step by step manner taking into consideration setup times and job splitting. However, the contribution of the work is the determination of a lower bound and heuristic method showing good performance. The computational results of the heuristic algorithm show a favourable performance evaluation on many randomly generated instances.

Bilyk, Monch and Almeder (2014) tackled the disruption problem of unequal ready times and precedence constraints for jobs in an identical parallel machine setting. An example of this problem is drawn from semiconductor wafer fabrication facilities. Mixed Integer Linear Programming (MIP) formulation has been provided for this problem and 'heuristic solution' approach was applied because it was considered as NP-hard problem. To solve the precedence constraints problem, a list scheduling heuristic was proposed and assessment of two metaheuristics; Variable Neighbour Search (VNS) and Greedy Randomized Adaptive Search Procedure (GRASP) performance was carried out. The VNS approach and a GRASP were designed to compare and demonstrate effectiveness by solving a large set of randomly generated problem instances. The result of the computational experiment revealed that VNS approach slightly outperformed GRASP-type heuristics. The paper considered identical parallel batch machines where the jobs have ready times. The paper also considered precedence constraints among the jobs and consider the following factor levels; number of job families, number of machines, maximum batch size, ready time, due dates and, precedence constraints. The knowledge gap found in this paper in two parts; the authors proposed new list scheduling heuristics that outperformed the time window decomposition proposed by Monch et al. (2005) by adding the precedence constraints. They also proposed and analysed a VNS scheme and a GRASP for the parallel batch machine.

Hazir and Kedad-Sidhoum (2014) addressed integrated batch sizing and just-in-time scheduling as causes of disruption problem where upper and lower bounds batch sizes were imposed. The study attempted to find a feasible schedule that minimises the sum of weighted earliness and tardiness penalties and setup costs, involving the cost of creating new batch. The problem is focused on a single machine scenario for which solution algorithm was developed for both single order and multiple order illustrations. The two solution algorithms for this problem are Optimal Batch Splitting Procedure (OBSP) for optimal schedule and Customer Order Assignment Algorithm (COAA).

The disruption in Karimi-Nasab and Seyedhoseini, (2013) study was about working speed in a lot-sizing and scheduling flexible manufacturing setting. They proposed an Integer Linear Programming (ILP) formulation for the simultaneous lot sizing and scheduling in a job shop environment. The objective was to decide optimal working speed. Several valid inequalities constraints were introduced to help reduce the non-optimal parts of solution space, dealing with some cutting planes. The proposed cutting planes which were used to find solution to the problem using two approaches such as cut-and-branch as well as branch-and-cut approaches. Among tools and techniques used is CPLEX 12.2 through which cutting planes performance was investigated on a set of randomly-generated test data. The computation results were presented that showed the performance criteria of the proposed cutting planes ranked using TOPSIS method.

In a two-machine flow-shop environment, Bukchin, Tzur, and Jaffe (2002) investigated disruption problems caused by detached setups and batch availability. When the setups are detached (disconnected), it causes longer production time since there would be numerous stops for re-setup during production. Also, shortage of available batch affect production scheduling, hereby causing delay in production. For this problem, average flow-time is considered for performance measurement, which is indicative of increasingly important manufacturing lead-time. The two-machine flow-show is a case where setup time is attached to each sub-lot (number of parts processed continuously on a machine with a single setup) and both variable unit processing times, and the sub-lot setup times, are machine-dependent. The contribution to knowledge from the paper is the consideration for case of general sub-lots or batches under the assumption of batch availability, which means all items in a sub-lot leave the machine together at the end of the processing of the last item in the sub-lot. The identified causes of disruption problems were solved by proposing a solution procedure based on an intuitive solution structure such as the Single Machine Bottleneck (SMB) property. The result of the investigation (computational study showing efficiency of the proposed technique) proves that the SMB property was satisfied in all optimal solutions. However, the study does not consider more than two machines and different part types. Rather, it focuses on demand as the number of parts waiting to be processed.

Dastidar and Nagi (2007) considered disruption that arise due to batch splitting in an assembly operation. In an assembly operation, production scheduling is disrupted when batch splits move through irregular production path as a result of dis-organisation. For this problem, two mathematical models and two heuristic algorithms were proposed. The two heuristic algorithms are batch splitting and batch scheduling algorithm. The batch splitting algorithms was developed using a pre-emptive scheduling algorithm after combining non-zero setup times. Also, the batch scheduling algorithm was developed based on a critical path algorithm for an operations network. One of the important considerations in the mathematical modelling is the move sizes for batches which determines the threshold for the batch size that needs to be built up before it can be transferred for the successor operation. The problem was tackled using two mathematical programming models, one representing a model with batch splitting and the other model with batch splitting and move size. An experimental illustration was presented to demonstrate the application of the combined approaches. The consideration for a heuristic algorithm approach was the result of the problem been Mixed Integer Linear Programming (MILP) problem. Therefore, the two heuristic algorithms were proposed, for both batch splitting and batch scheduling heuristic algorithms respectively. For different problem sizes, the computational results revealed that the proposed solution scheme can successfully solve the identified complex scheduling problem rather than using just a standard solver with failed solution within practical time limits. The contribution of this work is the inclusion of move size in disruption problem caused by batch splitting.

Disruption in production can be due to 'repetitive lots' as considered in Edis and Ornek (2009), who replicated the work of Jacobs and Bragg (1988). Repetitive lots is a situation where the same number of lots are repeated in a job shop. However, when there is an unequal size of sub-lots in a job-shop environment, it becomes a problem. , The two groups of researchers focused on obtaining equal sized sub-lots in a 10-product and 10-machine job shop environment. In Jacobs and Bragg (1988), the problem includes the queuing disciplines and aims to minimise the flow time. On the other hand, Jacobs and Bragg (1988) just investigate the benefits of lot streaming in job shops, Edis and Ornek (2009) analysed the effect of Transportation Queue Disciplines (TRQDs) on lot streaming problems in job shops. Jacobs and Bragg (1988) study does not consider optimising equal sub-lot sizes instead used simulation to compare the results of repetitive lots, queue disciplines and traditional methods. On the other hand, Edis and Ornek (2009) used uniform distribution to randomly generate weekly demand for each product type. Likewise, the machine routes for each job are assigned randomly. The performance measures determined for the products includes; number of operations, machine assignments, load-unload, setup, trip and processing time. They proposed a simple heuristic algorithm to tackle the lot streaming problem, which is related to splitting order quantities of different products into different Number of Equal Sub-lots (NES). The NES approach is also used to analyse the effect of sub-blots-related TRQDs for different performance measures.

The problem of assigning combined due-date, production and batch delivery scheduling for make-to-order production system and multiple customers was identified causing disruption in Rasti-Barzoki and Hejazi (2013). It is a situation where a common due date is assigned to all jobs of each customer and the number of jobs in delivery batches is constrained by the batch size. The objective of this investigation was to minimise the following; the sum of the total weighted number of tardy jobs; the total due date assignment costs and; the total batch delivery costs. The problem was NP-hard and therefore was formulated as an Integer Programming (IP) model. Among other tool and techniques adopted are heuristic algorithm and Branch and Bound (B&B) methods. The computational result of the IP through B&B method was compared with CPLEX of which B&B outperformed CPLEX. However, the paper has only taken into consideration batch delivery of finished products to multiple customers among other factors such as due date assignment.

Wang et al. (2012) studied disruption impacting the quality of product sequencing. The product quality is investigated in flexible manufacturing systems with batch production using a Markov chain model. The case study of an automotive paint shop was adopted for improving production quality improvability and quality bottleneck sequence. The work focused on quality improvability with respect to product sequencing and introduced the idea of improving product quality through re-sequencing. However, the work has only considered sequencing and re-sequencing measure as the only factor to improve product quality.

Rolon and Martinez (2012), adopt agent-based modelling and simulation for production management systems problem of unplanned disruptive events and disturbances such as arrivals of rush orders, shortage and delays of raw material as well as equipment breakdowns. They propose autonomic units to exist between shop-floor control and production planning gap. This was implemented for agility and responsiveness of the shop-floor of a multiproduct batch plant. In Herrmann (2013), the disruption problem relating to more restrictive retractions in flow shop scheduling was investigated. The study developed a simulation-based priority rules for the flow shop scheduling problem. It is an NP-hard problem, a kind of scheduling problem with no-buffer in more than two workstations running simultaneously. The developed model was implemented in a real-world application, a partly automated production line at Fiedler Andritz in Regensburg to produce filter with a lot size of 1. The simulation outcome of the processing time improves many priority rules significantly.

Petrovic and Duenas (2006) focused on uncertainty disruption in production but tackled production-scheduling problem of non-sequentially dependent parallel and identical production machines. The paper developed a model, which represented parallel machines schedule of which uncertain disruptions are inherent. The problem was considered using a new fuzzy logic-based decision support system and genetic algorithm. However, a decision support system RES-FRB for fuzzy predictive-reactive scheduling of identical parallel machines was developed. The predictive-reactive approach was defined as a two-step process, where the first step consists of adding idle time to the jobs' processing times to generate a schedule capable of absorbing the adverse effects of uncertain material shortages. The second step, which was based on rescheduling, answered two questions of ‘when to reschedule’ and ‘which method to apply’. A predictive schedule was therefore generated to minimise the effect of low impact disruptions while two reactive scheduling methods were proposed to deal with high impact disruptions. The developed system was applied to a real-life case study of Denby Pottery Ltd UK, a pottery company that manufactures a wide range of ceramic tableware products. The results showed that the variables, including time of disruption occurrence, duration of disruption, priority of the schedule efficiency and priority of the schedule stability are of great importance in making the reschedule decisions.

In Giunipero and Eltantawy (2004), disruption due to transportation problem was considered as damaging for supply chain to function. According to Guiffrida & Jaber, (2008), transportation disruption can cause late deliveries, which may lead to production stoppages costs, lost sales and loss of customer’s goodwill. Furthermore, a transportation disruption may affect the condition of the valuable goods in transit. Due to the rise of organized crime and terrorist activities, the cost of goods lost during transportation is estimated at billions of dollars per year, with manufacturers suffering losses amounting to approximately five times the value of those goods damaged or stolen. The floods that hit Bangkok in 2011 caused vast damage to inventories in sugar mills and firms faced increased raw material cost and shortages, partly due to transportation disruption (Fernquest, 2011). Managers are forced to seek cost effective ways to react to these unexpected occurrences, mainly to alleviate the damaging impact it could bring to the firm.

The disruption problems discussed in Kalir and Sarin (2001) is related to relaxing limitations of single batch, flow shop, and lot-streaming situation. The study identified there are several limitations in the lot-streaming models by many researchers, which affect the practicality of them in real-life. The objective function is therefore to minimise makespan and cost-based objective. An investigation of the objective function was carried out to determine the impact of transfer on the objective function, the impact of setup on the makespan objective and an algorithm for optimal solution for the makespan criterion was developed. The paper has contributed a way of splitting a lot to optimise performance under various measures of performance and setup time considerations.

Hoque and Kingsman (1995) dealt with a production system disruption problem concerned with fixed sequence. It is related to constant lot-size for production of single product requiring processing through series of manufacturing stages. It is also the case of a single setup at each production stage followed by continuous production of the whole lot in a serial production system. The objective was to minimise various parameters cost function such as setup cost, transportation and inventory. A heuristic solution procedure model was based on a modification of Goyal and Szendrovits (1986) model which enables a few properties that the optimal solution must satisfy to be determined, from which optimal solution of their problem was derived.

The records of disruptions caused by suppliers of raw materials are found in (Berk & Arreola-Risa, 1994; Li, Xu, & Hayya, 2004; Parlar & Berkin, 1991; Parlar & Perry, 1995), in which supplier availability has been modelled as one of the major disruptions in supply chain and hence affecting production process. Tomlin (2006) examines the optimal strategy for a single product system with two suppliers: one that is unreliable and another that is reliable but expensive. Schmitt, Snyder, and Shen (2010) and Chen, Zhao, and Zhou (2012) extended the work of Tomlin (2006) to study the system with stochastic demand. Furthermore, Schmitt and Snyder (in-press) conducted a study on the comparison between single period and multiple period settings for an inventory system subject to yield uncertainty and supply disruption. To do this, they extended the paper by Chopra, Reinhardt, and Mohan (2007) which only considered the single period case. Other variations of supply disruptions in stochastic inventory models are also available in literatures (Arreola-Risa & DeCroix, 1998; Li et al., 2004; Mohebbi, 2003; Moinzadeh & Aggarwal, 1997). Snyder et al. (2012) provides an extensive review of supply chain models with disruption.

2.3 External Disruptions Affecting Flow-Shop Manufacturing and Related Environments

One of the external sources of disruption on flow-shop is caused by customers' behaviour. Customers are considered a major external factor that can have influential impact on production. This is because they play vital role in making production decisions for flow-shop industry.

Lin et al. (2010) considered disruption problem through the influence of customer on specific quality level. The study relates to special production characteristics in a Thin-Film Transistor Liquid Crystal Display (TFT-LCD), and material to be used in a finished product which they termed 'customer preference' resulting into alternative bill of material (BOM). The paper presented what they called an Available-To-Promise (ATP) model that supported decision-making in order fulfilment processes for TFT-LCD manufacturing. A linear programming model was used to formulate the problem situation. Using the case study, the effectiveness and efficiency of the developed model was demonstrated and sensitivity investigation of TFT-LCD plant performance to changes in order batching interval was performed.

When customer make order substitution or return products, the production schedule is affected. This type of disruption was considered by Li, Chen, and Cai (2007). They studied the production planning in this regard and specifically investigated Capacitated Multi-period Two-product Production-planning with Remanufacturing and Substitution (CMTPRS). They developed a model that focused on substitutions and return products, which they termed 'remanufacturing'. Genetic algorithm was applied to determine all periods requiring setups for batch manufacturing and remanufacturing. They then developed a dynamic programming approach to provide the optimal solution. Numerical result of the proposed algorithm for performance evaluation was implemented using MATLAB platform, in which the simulations showed that the algorithm can be very effective approximation solution to CMTPRS in a reasonable computation time. The developed model was based on deterministic demand, rather than stochastic which varies randomly over time.

The constant need for changes of order requests has made customers involvement on production more crucial. This translate to dynamic customers behaviours disrupting production processes. Hsieh and Yen (2005) studied the implication of customer involvement on service providers' job stress. There have been clear relationship conflicts and damaging effect of customers' participation on production decisions. The request for changes in demand requirements increase the level of stress and disruption on production schedules. The change request from customers can be in form of order production, sequence and delivery process.

2.4 Disruptions Response Approaches

The different approaches adopted in the past to solve the problem of disruptions from different perspectives are presented in this section as it relates to the causes of disruptions on flow-shop related systems.

In Paul et al. (2014) develop a real time disruption recovery model for a two-stage production-inventory system. The objective of the developed model was to obtain an optimal recovery plan in real time, whenever the production system experiences either a sudden disruption or a series of disruptions, at different points in time.

Singh and Prasher (2014) propose a production inventory model over infinite planning horizon with flexible but unreliable manufacturing process and the stochastic repair time. Demand is considered as stock dependent and during the period of sale it depends on reduction on selling price. Production rate is a function of demand and reliability of the production equipment is assumed to be exponentially decreasing function of time.

Omar and Yeo (2014) proposed a production-repair inventory model with time-varying demand and multiple setups as disruptions. The model represented a known and finite planning horizon of both new and repaired items of finished product type. The objective of this study was to determine a joint policy for raw materials procurement, new items fabrication, and used items repair to minimise the total relevant cost in the model. Mathematical formulation of the proposed model was developed. The model was tested, and result presented using numerical examples and simple sensitivity analysis. The numerical solution showed the effect of changes in parameter values on the behaviour of the decision variables. However, the general optimality of the model, in terms of the sequence of production and repair runs was not investigated.

Chen et al. (2014) introduced a disruptions management model for a supply chain under strategic subsidy policy for the demand-stimulating inventory. This model consists of a manufacturer and a retailer with demand depending on the amount of inventory displayed on the retailer’s shelf. A disruption operation caused by a sudden change of market demand which is capable of changing decision makers’ original plan is considered. The objective of the developed model is to achieve a win-win situation for both parties with two kinds of disruptions considered; single-factor disruption and two-factor disruption situations.

Ben-Daya, As'ad, and Seliaman (2013) based their study on integrated production inventory and focused on raw material replenishment for a three-layer supply chain. The three layers consist of single supplier, single manufacturer, and multi-retailers, and dealt with joint economic lot sizing problem (JELP) in this context. The objective of this work was to specify the timings and quantities of inbound and outbound logistics for all parties involved. This was to minimise setup, chain-wide total ordering, raw material and finished product inventory holding costs. To achieve these objectives, a model was developed. The developed model was built to resemble the actual practice, which allows shipments of a lot to take place during production and not after. A derivative-free method was employed with mathematical model, which was used to derive a near closed form solution for the developed model. The result was presented using a numerical example for illustration. However, the developed model is only applicable for the case of deterministic demand and quantity issues has not been incorporated.

Xanthopoulos et al. (2012) propose a generic single period (newsvendor-type) inventory models for capturing the trade-off between inventory policies and disruption risks in a dual-sourcing supply chain network both unconstrained and under service level constraints, where both supply channels are susceptible to disruption risks. The work considered two suppliers with different procurement prices, disruption probabilities and consequences (order yield), which generally allows for one reliable and one unreliable supplier. The aim of the developed model is to determine optimal expected total profit of the retailer/wholesaler.

Hishamuddin (2012) who develop a disruption recovery model for a single stage production and inventory system, where the production is disrupted for a given period during the production up time. The objective is to determine the optimal production quantities and the number of cycles for recovery, to minimise the total recovery cost. Cauvin et al. (2009), propose an approach to minimise the impact of disrupting events on a distributed manufacturing system. This approach is based on analysing disrupting events and the characterising the recovery process, and on a cooperative repair method for distributed industrial systems. This will assist decision makers in the design of recovery decision processes with the aim of helping the actors of the system to improve their reaction time and to minimise the impact of the disrupting events on the whole system.

Chen et al. (2012), propose a model for periodic-review inventory system with disruption involving two suppliers. The two suppliers are classified as one unreliable regular supplier that may be disrupted for a random duration, and a reliable backup supplier that can be used during a disruption. The backup supplier service is utilised at unplanned moments, and its capacity to replenish inventory is considered limited. Setup cost and capacity are two main parameters considered for this model.

Barbati, Bruno, and Genovese (2012) presented a comprehensive review of related work in use and application of agent-based modelling. They focused on its use in proffering solutions to optimisation problems. The paper further gives details of agent-based peculiarity as a suitable method for simulating complex systems. The comparison of this model with classical heuristics approach and its impact in operational research and management science domains is provided. The outcome of the investigation review of the application of agent-based technology reveals that agent technology is increasing becoming popular and have been applied in various research areas such as; supply chain planning, transportation and logistics, production scheduling, general planning, and facility location and other related optimisation problems.

Karageorgos et al. (2003) proposed an agent-based approach for supporting production and logistics planning. Agent-based technology is considered very relevant in production planning and scheduling. This is because agents are capable of dynamic behavioural adaptation to changing requirements. The developed agent-based model not only support logistics and production schedules, but also considered related cost and availability of logistic service providers. The aim of this work was achieved using efficient negotiation mechanisms based on an extended contracting protocol. This approach was demonstrated with a case study of a virtual manufacturing company, which relates to optimisation of production planning. The paper however, delivered a holonic agent system capable of supporting a non-trivial integration of manufacturing and logistics service planning. Using this approach has allowed dynamic changing configurations of the virtual case study, as well as dynamic sourced offers for logistics services.

Sarker and Khan (1999) propose a model for disruption resolution based on periodic delivery policy. The objective of the proposed model is for optimal batch size for a production system. The model reflects the dependent relationship between raw material requirement and production quantity. The model also considered the relationship between finished products and its raw material availability. Lin and Gong (2006) consider the impact of random machine breakdowns on classical Economic Production Quantity (EPQ) model for a product subject to exponential decay and under a No-Resumption (NR) inventory control policy. The focus of this work is made on product manufactured in batches on a machine that is subject to random breakdowns to meet a constant demand over an infinite planning horizon.

The disruption relating to time-dependent failure on machine is considered in Iravani et al. (1999). It was the case of production inventory system consisting of M machines and K (K<=M) repair crews. The critical aspect of this disruption is that because of machine breakdown requiring repair, unsatisfied demands are lost. However, the objective of the proposed model is to minimise the sum of the average holding and lost-sales penalty costs. Paul et al. (2013) propose a disruption management model for a production inventory system that involves an imperfect production process and faces production disruption and demand uncertainty. The demand uncertainty is considered as a fuzzy variable while the imperfectness is expressed as process reliability. The objective of the developed model is to maximise the Graded Mean Integration Value (GMIV) of the total expected profit by using the model to obtain optimal recovery plan. Hishamuddin et al. (2014) propose a disruption recovery model for a two-echelon supply chain system under supply disruption. The developed model is to determine the new schedule in real-time that minimises recovery costs.

Duncan et al. (1999) focused on demand of products with unknown parameters. They developed a model for adaptive production planning of failure-prone manufacturing systems. The paper described market demand of products as one of the key factors that determines the production strategy of a manufacturing firm. It highlighted various ways of formulating the demand processes. The paper however investigated a class of production planning problems with incomplete demand information. The developed model therefore represented the demand problem to be either the sum of an unknown rate and small white noise or the sum of a hidden Markov chain and a small white noise. This problem was to find the rate of production that minimises the overall costs of inventory/ shortage and production. To solve this problem, an algorithm was developed to define a family of estimates for the unknown demand processes. Adaptive controls were also constructed based on the family of estimates using unknown parameters. The result showed the adaptive control to be nearly optimal as the noise in the demand process tends to zero.

2.4 Application of Inventory Control Model for Disruption Problems

This section presents previous records of the implementation of inventory model in disruption related problems. This section is presented to explore the associated of disruption with inventory, as part of the solution strategy in this study.

Fu-gui, Hui-mei, and Bing-de (2012), base their work on the finished product inventory control. They decided to find a balance between inventory cost and stock holdings. An agent-based simulation model was developed for a single point inventory system of supply chain. There are two strategies for replenishment described: continuous and cyclical strategies. Cyclic strategy checks the status of the inventory on a fixed cycle, divided into (t, R, S) and (t, S) policy, whereas continuous strategy is based on the continuing changes in the level of inventory and its divided into (Q, S) and (Q, R) policy. The latter was chosen to represent two continuous replenishing strategies called (Q, R) and (R, S) in terms of random and time constraint customers' demand. The symbols are different inventory policies at different quantities and re-order points for replenishment. The two strategies differ in the quantity of order. They acknowledged four main methods of modelling complex problem of this nature: System Dynamics model, Petri Net, Agent-based modelling and simulation and Object-Oriented technology. However, they adopted agent-based method alongside other tool and techniques like AnyLogic software. The optimisation was developed using OptQuest Optimisation Engine due to its ability to find the best parameters of a given model in relation to certain constraints automatically. The results of the simulated model revealed that (R, S) strategy is better than (Q, R) because a minimised finished products inventory cost was achieved with its analysed optimal result.

Rossi et al. (2011) tackled the problem of non-stationary stochastic demand and service level constraints for single-location, single-product production/inventory control. The work proposed an efficient approach for computing Replenishment Cycle policy parameters under these conditions. The Replenishment Cycle policy is known as a popular inventory control policy typically used for dampening planning instability. They developed and algorithm for computing optimal (Rn, Sn) policy parameters. The approach adopted combined two existing techniques of Tarim and Kingsman (2004), which are Dynamic Programming and State Space Relaxation. These was used to obtain an effective approach for computing (Rn, Sn) policy parameters. The experimental results showed that the proposed approach could solve instances over planning horizons comprising hundreds of periods.

Wang (2009) identified the disruption caused by unknown demand, which affect inventory level control of multi-echelon supply-chain distribution network. The aim of the work was to find methods to address this problem in terms of the traditional Distribution Requirement

Planning DRP's weaknesses and to improve the performance of DRP systems. However, a new method based on fuzzy model with fuzzy input data was presented. A continuous review model was also developed tagged: Continuous Review Inventory Model (CRIM). The model depicted inventory level control for supply and forecasted possibility of demand, varying channel multi-echelon retail type orders over the medium term of lead-time and related parameters. The method focused on inventory control of a Distribution Requirement Planning (DRP) supply chain management. The paper dismissed the use of precise number approximately as representative of a fuzzy number because it claimed the method could not reflect the property of fuzzy inventory control number fully. It introduced new method which used the interval mean value concept, initially proposed by Dubois and Prade (1987), as a transformation technique for reducing a fuzzy number into a closed interval. The interval mean value was introduced to manage material flows in multi-echelon supply distribution networks. The new method combined the interval mean value concept with possibility fuzzy set theory. LINDO computer package was used to run the fuzzy CRIM model to obtain a crisp solution for solving the practical demand. The fuzzy model results yielded optimum values, which means maximum order quantity under a minimum of total cost, and channel performance.

Hsieh, (2004) developed an inventory model under disruption of uncertain demand. The paper assumed a fuzzy demand and fuzzy lead-time on a cycle in fuzzy inventory control system to be trapezoidal distribution and trapezoidal fuzzy number defined by decision maker. Two models were proposed, the first model was for a fuzzy inventory under order quantity preference. The model represented fuzzy total annual inventory cost, which is the sum of total annual holding cost and fuzzy total annual setup cost. The second model proposed was for fuzzy inventory under safety stock, which was based on fuzzy total annual safety cost combined by total annual holding cost of safety stock and fuzzy total annual stock out cost. By using both Function Principle and Graded Mean Integration Representation method for both computing and representing fuzzy total annual inventory cost, an optimal order quantity was obtained. Likewise, the results of the second model showed an optimal reorder point and optimal safety stock.

Hsieh (2002), proposed two fuzzy production inventory models: fuzzy production quantity and fuzzy parameter for crisp production quantity. The purpose of this paper was to find optimal solutions of these models. The associated disruption problem was identified as unknown demand types. Hence, the paper took into consideration fuzzy parameters that included fuzzy demand, fuzzy demand rate, fuzzy inventory cost, fuzzy setup cost and fuzzy production rate. A case study example of Brown Manufacturing, which produces refrigeration units for commercial use in batches, was adopted for model validation. Lagrangean method extension was used to solve the problem of inequality constraint while Grade Mean Integration Representation method was used to ‘defuzzify’ fuzzy total production inventory cost. Fuzzy arithmetic operations of Function Principle of the fuzzy total production inventory costs of the developed models are also proposed. The result showed that the optimal solutions for the fuzzy parameters are all crisp real numbers and because of this, the proposed model specifically met classical production inventory models.

Samanta and Al-Araimi, (2001) developed a periodic review model using fuzzy logic for inventory control for disruption of variable demand of order quantity. The developed model was a combination of proportional-integral-derivative (PID) control algorithm and fuzzy logic. The purpose of the model was to simulate the system with the aim of maintaining finished product inventory at the desired level in variable demand condition. Among the tools and techniques used was theoretical approach based on production-inventory System Dynamics. A clock function of MATLAB was used to generate simulation timing. The simulation model was built using Simulink and Fuzzy Logic Toolbox. A case study of a packaging organisation located in the Sultanate of Oman was adopted whose real-life data was used to validate the simulation results. The results showed the effectiveness of the developed model as the inventory was maintained reasonably well within the desired level.

Gen, Tsujimura, and Zheng (1997), developed a continuous review model to solve inventory control problem of demand. The developed inventory model was based on uncertain demand order quantity. The model was developed using fuzzy input data. They represented the input data for their model by triangular fuzzy numbers. To arrive at a real number result instead of fuzzy numbers used as inputs, the fuzzy result was transformed into crisp output. This was possible with the concept of interval mean value proposed by Dubois and Prade (1987). On the other hand, Hooda and Raheja (2014) used Positive Ordered Transforming Formula (POTF) techniques to transform crisp data into vague data. A new method, which combined probability theory with the concept of interval mean value, was presented. The crisp solution results showed that the maximum interval order quantity is possible with minimum the total cost.

2.5 Application of Agent-Based Model for Problems in Flow-shop Related Environments

The adoption of agent-based modelling and simulation technique in the flow-shop manufacturing field of study is not a new concept but is however increasingly gaining a lot of attention recently. In the past, researchers have implemented its usage in various aspects of flow-shop manufacturing, such as scheduling, production control, and inventory among others. However, the way in which this method has been used varies from one problem domain to another. This section discusses the review of the application of Agent-Based in flow-shop related system for design, planning and scheduling. In this study, the review of agent-based technology on enterprise integration is of concern as it relates to the proposed integrated framework to the solving the current research problem.

Rolon and Martinez (2012), adopted agent-based modelling and simulation for production management systems problem of unplanned disruptive events and disturbances such as arrivals of rush orders, shortage and delays of raw material as well as equipment breakdowns. They proposed autonomic units to exist between shop-floor control and production planning gap. This was implemented for agility and responsiveness of the shop-floor of a multiproduct batch plant.

Barbati, Bruno, and Genovese (2012) presented a comprehensive review of related work in use and application of agent-based modelling. They focused on its use in proffering solutions to optimisation problems. The paper further gives details of agent-based peculiarity as a suitable method for simulating complex systems. The comparison of this model with classical heuristics approach and its impact in operational research and management science domains is provided. The outcome of the investigation review of the application agent-based technology reveals that agent technology is increasing by becoming popular and have been applied in various research areas such as;

- Supply chain planning
- Transportation and logistics
- Production scheduling
- General planning
- Facility location and other related optimisation problems

It also reveals that its real-life applicability has cut across many industries such as; manufacturing, transportation service, electronic devices, lumber, energy, fashion, information and communication, aerospace as well as automotive industry.

In their work, Li, Shan, and Lui, (2011) apply multi-agent-based framework for dynamic shop floor reconfiguration. With the combination of mathematical programming model, process planning is taken into consideration and a cooperative co-evolutionary algorithm to coordinate the resource assignment among agents. The proposed model is developed using combined multi-agent and mathematical programming method to decompose and optimise the problem of reconfiguration and considering alternative process plans. They suggest the potential result of their work to help solve the problem of shop floor reconfiguration with complex and dynamic interactive structure.

Li, Zheng, and Yang (2010), presented a paper that dealt with a multi-agent architecture of agile manufacturing system and hybrid strategy for shop floor scheduling. They propose a distributed multi-agent-based manufacturing structure. The structure which is self-determinant and grounded distribution on multi-agent as well as control and harmony grounded on hierarchical structure or dynamic logical unit. The proposed structure uses fuzzy theory and method to study a hybrid shop floor scheduling strategy that combines fuzzy programming with fuzzy contract net protocol, developed to specify problem-solving communication and control. The result shows precision of static programming and flexibility of contract net protocol. A computational experiment to justify the feasibility and efficiency of the hybrid strategy is presented.

Agent-based techniques have also been used in manufacturing shop-floor scheduling problem (Wang et al. 2008). They propose a distributed manufacturing scheduling framework at the shop floor level. Their modelling framework includes the multi-agent system modelling of work cells, service oriented integrated of the shop-floor, distributed shop floor control structure and dynamic distributed scheduling algorithms. The framework has been demonstrated in real-time scheduling of two work cells.

Ou-Yang and Chang, (2005) apply the concept of agent-based approach to bridge the gap between product data management (PDM) and enterprise resource planning (ERP) software application modules. The PDM manages the product data and product development process, while the ERP acts as the main tool for order, production and inventory related processes. The paper established the use of agent-based approach for collaboration activities between PDM and ERP. To achieve that, a three-stage framework was proposed to develop the agent-based collaboration system. This includes, the concept stage, in which modelling tools such as VAD and eEPC were used to capture collaboration requirements between PDM and ERP. The design stage, in which a UML-based analysing method MaSE was used to develop the agent-based system. In addition, an agent-based development tool ZEUS was used to generate agent code. Finally, the implementation stage, where a PDM/ERP collaboration system was developed to support the designer in making decisions about the replacement parts requirement analysis. The result of the proposed framework was verified using an agent-based design tool along with two commercial ERP and PDM modules.

Wang et al. (2003) proposed a design methodology for multi-agent systems in the area of production scheduling. The research focus on systemic framework of CAPP and scheduling integrated multi-agent system according to design methodology. In this multi-agent system, agent model, composition model and cooperation model are identified and discussed. Likewise, static composition model and dynamic running model of CAPP and scheduling integrated system are presented. Consequently, CSIMAS, CAPP and scheduling integrated multi-agent prototype system was developed to illuminate system model. The developed model was tested using multiple non-rotational parts in distributed process planning and scheduling environment.

The agent-based enterprise integration of Yu and Huang (2003) was implemented in NTU, Taiwan. They modelled the order fulfilment process (OFP) of the foundry fab using General Message-Passing Platform (GMPP). The developed model is important to find a bottleneck in the semiconductor foundry fab process. The study proclaimed the possibility of an agent-based technology in a distributed environment to possess the properties of a distributed system. The model was validated using useful information for decision support systems shown in the simulation results. Many computerised assistants known as Intelligent Agents (IAs) were developed by Pan and Tenenbaum (1991) as agent-based integration framework for a real-life enterprise. The presented framework enables interaction of human and intelligent agents (IAs) to facilitate the information flow and decision making in real-life enterprises. In this framework, complex enterprise operations were divided into a collection of simple tasks. Each task was modelled in cognitive terms and entrusted to an IA for execution. This approach proofs viable because it is buildable and maintainable by end-users in a real-work distributed artificial intelligence.

Riha et al. (2001) focused on agent-based production planning using the ProPlan technology. ProPlanT is a multi-agent production planning technology developed by ExPlanTech project. The aim of the paper is to introduce, customise and exploit this ProPlanT multi-agent system research prototype in two specific industrial enterprises. An agent driven service negotiations and decision process based on usage-centred knowledge about task requirements substitutes the traditional production planning activity. In this approach, a methodology for integration of project-driven production planning based on agent-based approach within the existing enterprise resource planning system was introduced. The developed system is said to have the ability to facilitate optimisation of resource utilisation and supplier chain while meeting the customer demands.

Burke and Prosser (1991) developed a distributed asynchronous system, and researched hierarchical architecture with agents representing resources, resources groups, and a scheduling process. In the DAS, the scheduling problem was decomposed both functionally and spatially across a hierarchy of communicating agents where each agent exhibits the properties of opportunism, reaction and belief maintenance. Each agent represents a unique software process, all of which could run at the same time. The developed agent system works such that each agent can react to a change induced by other agents and negotiate to achieve a common global goal.

The combination of Agent-based technology with other techniques to form an integrated entity or solution framework are evident in the previous studies. Other related studies are discussed further below.

In their work, Cost et al. (1999) adopted the use of agent-based technology for enterprise planning and execution. The development was based on a Java-based multi-agent development platform called JACKAL. JACKAL is said to support intelligent integration of enterprise planning and execution using a simple business scenario. The JACKAL tool is used with KQML agent communication language because of its flexibility, conversation management facilities, ease of integration and blackboard style interface. The tool proofs to be valuable in developing agents for manufacturing information flow.

Gray et al. (1998) researched on use of agent-based technology in transformation and reuse of knowledge with mediator agents as knowledge brokers. The research was based on Knowledge Reuse and Fusion/Transformation (KRAFT) consortium working together to design and build a system capable of intelligent mediators and can act as knowledge brokers. It is also used to develop a system that can transform knowledge to make it reusable by powerful problem-solvers at various sites on the network. Agent-based system was established as a problem-solving solution in terms of handling distributed design constraints.

Budenske et al. (1998) adopted agent-based technology in enterprise integration. Their main features include middleware architecture. The work addressed the problem of exchanging modelling information between multiple legacy applications, not initially developed to be interoperable. This approach made it possible for information to be shared by multiple applications. This is done through intelligent agent-based common communication protocols and common model and process semantics and structure called the middleware.
Peng et al. (1998) also used agent-based technology for enterprise integration. They tackled the problem of lack of interoperability of enterprise wide integration in manufacturing establishments. This is because the production management system comprised of disconnected planning and execution processes. They proposed an agent-based framework for an intelligent enterprise integration. The framework cooperate with each other, human manager and the other management systems to arrive at timely decisions in dealing with various enterprise scenarios. The result of the implemented framework was demonstrated through an integration scenario of real management software systems.

From literatures, agent technology has been associated with complex problem solution. However, its choice is logical when such type of problem is evident. Having studied various related disruptions within similar industrial segments and different approaches implemented in the past, it is essential to draw attention to some overlooked but crucial areas in these studies. In the next paragraph, the critiques of some selected studies are presented.

2.6 Critiques and Gap in Knowledge

Below in Table 2.1, summary of the selected literature which shows the author, causes of disruption problems and tools and techniques applied to solve them are highlighted.

Table 2-1: Summary of selected causes of disruptions problems with adopted tools and techniques

	Author	Disruption Problem	Tools & Techniques
1	Bilyk, Monch and Almeder (2014)	Unequal ready time and precedence constraints of jobs for batch scheduling for identical parallel machines.	Mixed Integer Linear Programming, Metaheuristics algorithm
2	Bukchin, Tzur, and Jaffe (2002)	Detached setups and batch availability of lot splitting scheduling in two-machine flow-shop.	Single Machine Bottleneck (SMB) property
3	Dastidar and Nagi (2007)	Assembly operation batch splitting and batch scheduling including movesize to batch splitting	Mathematical modelling, Heuristic algorithm, MILP
4	Jacobs, F. R., and Bragg, D. J. (2016)	Equal size sublots for a 10-product, 10-machine stochastic job shop lot streaming to minimise flow time	Simulation method
5	Edis and Ornek (2009)	10-machine 10-product job shop to analyse effect of Transportation Queue Disciplines (TRQDs) on lot streaming	Heuristic algorithm
6	Li, Chen, and Cai (2017)	Production planning of Capacitated Multi-period Two-product Production-planning with Remanufacturing and Substitution (CMTPRS) for deterministic demand	Genetic Algorithm, MATLAB, Simulation, Dynamic programming
7	Lozano and Medaglia (2014)	Scheduling of parallel machine with sequence-dependent batch and product incompatibilities in bottleneck workstation to maximise utilisation and minimise delay	Heuristic approach: MILP and GRASP
8	Surjandari, et al. (2015)	Batch scheduling in assembly job shop with parallel machines that produce multi-item multi-level products to minimise flow time (FT)	Java language, Heuristic algorithm
9	Wang et al. (2012)	Product quality in flexible manufacturing systems with batch production to improve quality performance through product re-sequencing	Markov chain
10	Rasti-Barzoki and Hejazi (2013)	Combined due date assignment and production and batch delivery scheduling for make-to-order production system and multiple customers to minimise the wei ghted number of tardy jobs	Heuristic algorithm, Integer Programming (IP), Branch and Bound (B&B) method, CPLEX,
11	Lin et al (2016)	Considered the influence of customer on specific quality level and material to be used in a finished product which they termed 'customer preference' resulting into alternative bill of material (BOM) for a special production characteristic in a Thin-Film Transistor Liquid Crystal Display (TFT-LCD)	Linear Programming
12	Yalaoui and Chu (2017)	Like Lozano and Medaglia (2014), They also considered sequence-dependency but for setup times for a simplified real-life identical parallel machine scheduling with sequence-dependent setup times and job splitting to minimise makespan	Heuristic algorithm, Little's method

Also, in Table 2.2, the types of disruptions discussed by different authors are classified based on the corresponding industries. Basically, the table maps the type of industries against the disruption types indicating the different studies that focused on them.

Table 2-2: Summary of selected industry and associated disruption types.

Disruption /Industry	Logistics	Supply Chain	Transportation	OEMs	Production	Retails
Raw material shortages					Xia, Xiao, and Yu (2004)	
Supply delay	Ketkar and Vaidya (2012); Bala (2014)	Vakharia and Yenipazarli (2008)				Xiao and Yu (2006)
Machine breakdown					Lin and Gong (2006); Schmitt and Snyder (2012)	
Order cancellation		Cauvin et al. (2009)			Yeo & Yuan, (2011)	Chen-Burger (2012)
Order defect		Qi (2009)				
Change in sequence					Chen & Xiao, (2009)	
Change in due time						
Resources shortage		Chopra and Sodhi (2014)			Paul & Essam, (2014)	Xiao & Qi, (2008)
Rush order	Arisha (2010)	Arisha (2010)	Arisha (2010)		Taleizadeh et al. (2014)	

As clearly highlighted in the table, majority of the production disruption types have been covered in the listed industries as found in literature. However, the disruption problem that impacts the OEMs system has received no direct attention from previous studies. This is the focus of the study, which shows a significant contribution specifically in the OEM flow-shop sector. Furthermore, Table 2.2 also reveal the types of disruption which help identify the area already covered in literature in terms of disruption types and corresponding industry types. It reveals the gap in knowledge that has been successfully discovered in this study.

Based on the investigation of related and relevant literature in this research area, there are gaps acknowledged. Majority of the previous studies focused on the production disruption problems under different industrial perspective and of course different disruption types. Although several studies developed disruption resolution and recovery models to tackle the occurrence of their named disruption types in the selected domain, they have not covered the entire problem possibilities. No study has been found that models the event of customer engaging in parallel production causing disruption in OEMs manufacturing environment. More so, most studies focused on other types of production disruptions

In some cases, previous studies considered single disruption in production and a very few based their study on a series of disruptions at random occurrences, but none have considered the combination of three unique disruption types which is found applicable in real-life scenario. Interestingly, no study has been found to develop a replenishment strategy that uses inventory to recover from the combination of three unique but practical production disruptions (discussed in this study) in a parallel operating flow-shop OEMs system.

- ❖ Like Edis and Ornek (2009) problem, each product's daily demand is considered fixed demand until there is a change from customer. The routes of the products on the machines are constraints based on job type. The setup time, number of operations, machine assignments, load-unload, trip and processing time, work-in-progress, and inventory limit are determined for the products. But unlike Edis and Ornek (2009), production batch quantity and sequence decision are subject to customer's changing requirement. This is a contribution to this kind of problem which, to the best knowledge of the researcher, has not received enough attention in this respect.
- ❖ Also, Lozano and Medaglia (2014) consider sequence-dependent processing time, batch capacity constraint, machine capacity, incompatible product families and additional resources all related to parallel machine workstation. Unlike Lozano and

Medaglia (2014), this research considers additional constraint which is the demand sequence from customer that affects the constraints already considered in Lozano and Medaglia (2014).

- Unlike Rasti-Barzoki and Hejazi (2013) that addressed a scheduling problem for batch delivery of products to multiple customers, the current research is considering the problem of sequence delivery in respond to customers' continuous changing requirements.
- Like Lin et al (2010) that study the influence of customer on quality level and material specification for finished products, the current research is considering the influence of customer on product sequence and quantity.
- Unlike the current research that study unfixed sequence of shipment and resultantly of manufacturing stages, Hoque and Kingsman (1995) has considered equal and unequal batch shipments for a single product with multi-stage production and most importantly related to fixed sequence of manufacturing stages.
- Also, the current research considers constant messaging updates that would enable production planner, customer end, inventory and flow-shop to interact to make up-to-date decision since customer requirement is continuously changing.
- Most importantly the current research for production scheduling with changing sequence and quantity has taken into consideration the inventory control in responding to the problem and making adaptive production decision.

Significantly, the change in delivery due 'date' disruption in previous studies was considered as a function of date (i.e. 24 hours' time window). But in this study, change in delivery due 'time' is emphasised and it is viewed as time function (i.e. in minutes of day) in OEMs flow-shop. The uniqueness of this study is based on three disruptions:

1. Change in sequence of production
2. Order cancellation, and
3. Change in order delivery due time.

The random combination of these disruptions in the perspective which has not be observed before in OEMs flow-shop where customer assembly line run sequentially and concurrently with the OEM flow-shop. Therefore, this study attempts to fill the knowledge gap by proposing an integrated framework. The framework which embeds three main entities (Agent-Based simulation, inventory control and adaptive heuristic algorithm) has a resolution platform. The platform to investigate the impacts of random combination of three disruptions specifically in OEM flow-shop and aim to minimise their impact to enhance customer order satisfactions.

Chapter 3: Methodology

The Development of Simulation-Based Heuristic Optimisation for Inventory Replenishment on Production Disruption in Manufacturing Scheduling System.

3.1 Introduction

This chapter extends some of the previous production and scheduling research by capturing customer-imposed production disruptions, delivery due time, change in sequence and cancellation disruptions that emanate from customer-side uncertainty within an integrated agent-based modelling and heuristic framework.

In the chapter, the methodology adopted in the study for solving the identified manufacturing production disruption problem is presented. It unveiled the proposed solution strategy and how it is applied in tackling the research problem. The approaches used to develop the manufacturing disruption scenarios through agent-based simulation is clearly defined. The proposed heuristic optimisation of replenishment strategy is explained as it is being incorporated into the system.

The way in which research is carried out is very significant to the outcome of it. Tools and techniques serve as baseline in which research data are been executed with the main objective of solving the research problem. In manufacturing environment, the aim is to fulfil customers' demand in due time, at right sequence and quantity, irrespective of disruption occurrences. This is in quest to remain competitive in a continuously changing complex global business environment. To contribute in the achievement of this goal from both academic and industrial perspectives, novel approach is introduced in this study and it is been explained using the methodology development framework shown in Figure 3.1 below.

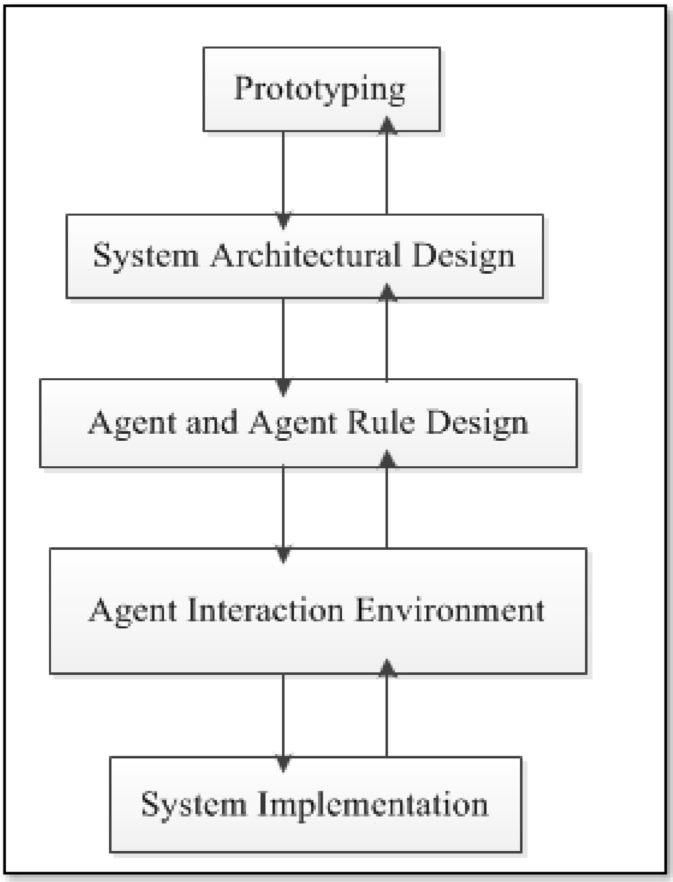


Figure 3-1: The Methodology Development Framework for the Proposed System.

- The ***prototyping*** stage development comprises of the proposed production disruption-inventory replenishment framework which underlines the concept explored in this study.
- The ***system architectural design*** stage follows the concept of the typical input-process-output system model.
- The ***agent and agent rule design*** discuss the agent-based operations. It details agents' attributes and behaviour within the simulation environment. It also discusses the rules they follow to achieve the autonomous capability, which is one of the main features of agent-based simulation approach.
- In the ***agent interaction environment*** stage, various agents' interactive activities within the simulation environment are detailed. The messaging system that allows information to be shared in the system is explained with an illustration.
- In the ***system implementation*** stage, agent-based simulation is integrated with the proposed heuristic optimisation to implement the inventory replenishment strategy

that is ultimately proposed in this study. The implementation stage goes further to demonstrate how the proposed approach is been applied for the research problem.

In the next section, the proposed methodology framework that forms the basis for the research problem resolution is presented.

3.2 Production Disruption- Inventory Replenishment (PDIR) Framework.

The framework in Figure 3.2 is proposed to illustrate the novel idea representing the research problem solution pathway. In the framework tagged Production Disruption- Inventory Replenishment (PDIR), there are components which were linked to show logical overview of their relationship to solve the identified research problem.

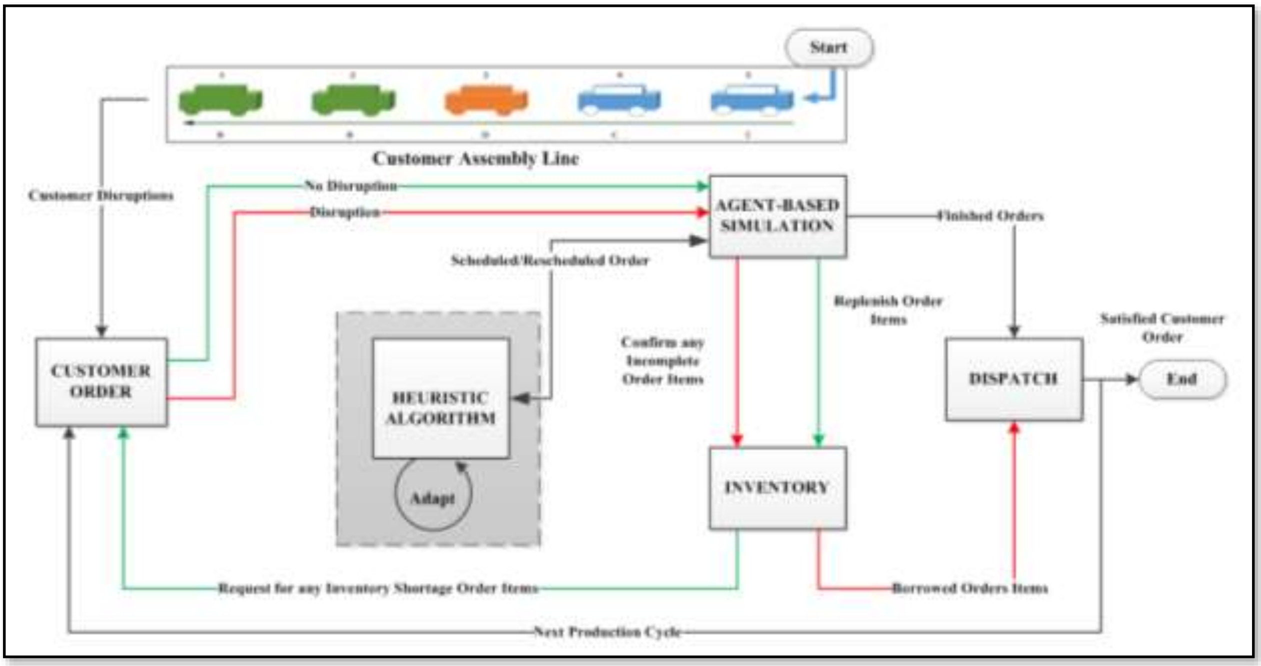


Figure 3-2: Production Disruption-Inventory Replenishment framework.

The PDIR framework correlated the flow in the research problem description. It is used to represent the real-life manufacturing disruption problem scenario. The main components of the PDIR framework that are significant to the achievement of the eventual outcome are; the agent-based simulation module, heuristic algorithm optimisation and the inventory module. These components were integrated to generate a novel solution strategy and form the developed system that has been presented in this study. The way in which the PDIR framework operates to achieve the research goal is described in the next section.

3.2.1 Description of the PDIR framework

Customer assembly line uncertainties trigger disruptions on the flow-shop operations. These uncertainties caused changes in order requirements and disrupts and disrupted the operation schedules. In an ‘ideal’ situation where there is no disruption as indicated by the green path, production processes experiences smooth running operation. . On the other hand, the red path indicates the disruption pathway, for which the framework is proposed to tackle. The flow process of the framework comprises of the following entities as described below:

- Start
- Customer order
- Heuristic algorithm
- Agent-based simulation
- Inventory
- Dispatch
- End

The start: initiates demand requirements based on customer assembly production line, which is sequence job processing and uncertain in nature, therefore causing production disruption. This type of assembly line operates in a flow process that can disturb and force re-sequencing of jobs. This process therefore dictates the way orders are requested by customer.

Customer order: can be received in two scenarios such as; No disruption order and disruption order:

> ***No disruption order***: customer order is without disruption possibilities when the requirements are unchanged throughout the production process within specified production cycle time.
>
> ***Disruption order***: Customer order causes disruption on the flow shop when there are changes in requirements such as sequence, time of delivery or order cancellation due to unforeseen circumstances on the customer's assembly line forcing a swap which means a later job preceding the earlier. This forms the basis for change in sequence and delivery due time.

Heuristic algorithm: is used to indicate the presence of order sequence scheduling and rescheduling algorithm in the case of disruption scenario, after reaching the simulation environment. In this way to provide adaptive production schedules that enable efficient utilisation of flow-shop resources such as machines, materials and operators. The algorithm can accommodate and adapt to production disruptions.

Agent-based simulation: is present as an autonomous system environment where production processes are replicated, accepts production inputs (disruption order and input parameters), processes them and produce outputs in the form of Key Performance Indicators (KPIs) of the system. The autonomous capability of the system helps assigning orders to machines as well as operators by identifying and matching agents (order, machine, and operator) behaviour and attributes. The agent-based system also evaluates production cycle time and isolate order items that will not meet customer dispatch due dates due to disruptions. By isolating these products, it sends confirmation for shortage order items (quantities) to the inventory storage for order item borrow quantities to complete production. The activities of the agent-based simulation in this manner would help satisfy customer demand in due time and without delay. The system also receives update from the inventory requesting borrowed order item to be replenished.

Inventory: is introduced to support the production against shortages that might be caused by disruption. It completes shortage orders and is been replenished for number of order item borrowed. Borrowing of order item becomes necessary due to disruption that renders customer requirements unsatisfied. The inventory is linked with customer order as shown in Figure 3.2 for the purpose of replenishment. This is to allow scheduling of replenishment order as new customer orders arrive. This is the way inventory requests for its shortage orders that was borrowed.

Dispatched: At this stage, completed orders that meet requirements of time and sequence (inclusion of finished and borrowed order) are ready for delivery

End: terminates production cycle, after which customer orders and inventory requirements have been satisfied.

3.2.2 The framework processes

The system framework was developed to operate as a typical flow process, but adaptive with the aim of adequately satisfying customer order (by delivery orders that meet due date, and required sequence) despite production disruptions, while ensuring smooth operation of the production process of the flow shop. The system process is triggered by order demand coming through from customer's assembly line. Customer demand is in specified sequence and due time as dictated by the assembly formation. This demand order can be disrupted depending on the various constrains that could impact customer's assembly line. The order demand without disruption goes through a normal production scheduling process. However, heuristic algorithm for production scheduling process accommodates and adapts the disrupted orders in terms of change in sequence, cancellation and due time change which emanates from customer assembly line constraints. The heuristic algorithm provides a proper/viable production schedule for flow shop simulation process. This heuristic algorithm schedule is significant to enhance efficient utilisation of production resources such as machines, orders and operator in the simulation process. Resource allocation is an important aspect of production scheduling. The autonomous capability of the agent-based system is significant in assigning scheduled order to resources through attributes and behavioural matching of order and resources. This technique allows order to identify specific machine as well as specific operator skill set, enough to work on specific machine and job. One important function of the agent-based system in the process is the ability to identify and report order that would not meet customer requirement. The system isolates and drops such order before requesting for shortage order from the inventory to complete customer order in sequence, and due time. The inventory serves as an operational storage facility for all order types where shortage products can be borrowed to complete and satisfy customer order demand. In as much as the inventory facility has a shortage limit, a replenishment request of any borrowed order is constantly reported and raised for replenishment in next possible run. In this case, the shortage orders are replenished using the 'replenishment strategy' proposed in this study. The finished orders as well as any borrowed quantities (to complete the order) all reach the dispatch node where customer demand is said to be successfully satisfied and end or the next production cycle can commence if there is any. In the next section, the architectural model of the system is presented. The various activities of the proposed framework are done and made possible within the adopted agent-based simulation approach, which is discussed in the next section 3.4. Based on the proposed methodology for the study, the next section presents the architecture model of the proposed system.

3.3 The architecture model of the proposed system

The proposed system architecture model in Figure 3.3 comprises of a main agent-based simulation model integrated with the proposed heuristic optimisation algorithm module. The function of the module integration is to enable order rescheduling as they are been allocated by the agent-based simulation.

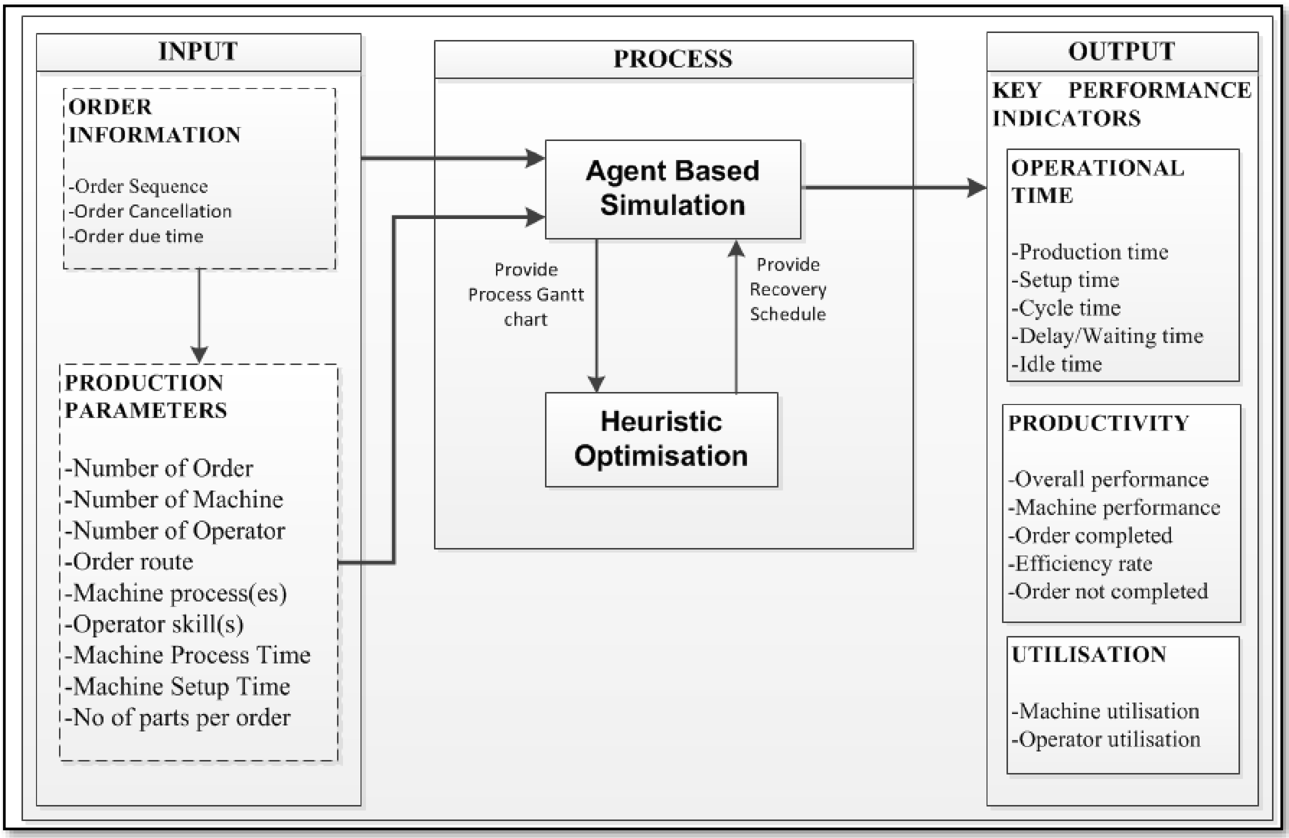


Figure 3-3: Proposed System Architecture Model.

The model depicts the traditional input-process-output (IPO) model.

Input: The input contains the order information obtained from customer through primary data collection method. It also contains other production parameters such as the machine process time, number of orders, number of operators, machine setup time and other flow shop requirements to commence production process.

Process: The process part consists of the integrated agent-based simulation and heuristic optimisation which is the core of the system. The simulation and the heuristic were incorporated such that order-machine-operator relationship could be optimised and for disruption to be accommodated and adapted to obtain a disruption-free output. The heuristic algorithm was selected to handle the rescheduling operation which is possible while the simulation is running.

Output: The outputs, as shown in the model (Figure 3.3) are the number of performance criteria known as key performance indicators (KPIs). These KPIs are categorised into operational, productivity and utilisation performance of the system. These are to enable performance analysis of the outcome of the study based on:

- Operational time
- Resources allocation
- Resources performance
- Resources utilisation

The output was designed to detect the most significant performance criteria that help in achieving the ultimate goal of the study which is translated in terms of the number of completed and replenishment order to satisfy demand and inventory level respectively. In the next sections, the proposed Production Disruption- Inventory Replenishment (PDIR) Framework developed from the system architecture model is discussed.

3.4 Agent Based Simulation

This section presents the development and implementation of the ABM approach as incorporated in the PDIR framework of manufacturing process scheduling for the system simulation. Agent-Based Simulation approach has been demonstrated in manufacturing system environment point of view to establish a potential relevance for this purpose (as discussed in the literature review section).

The choice of adopting the agent-based simulation approach as a method in this research was inspired by the investigation of the related studies. In the transportation industry, Evans and Elston (2013) applied the use of agent-based modelling in a disruption problem. Specifically, the investigation conducted in the manufacturing industry revealed the implementation of agent-based simulation modelling approach in the work of Rolon and Martinez (2012) and Li, Shan, and Lui, (2011) amongst others related studies.

In the past, production-inventory scheduling problems have been tackled using various well-known simulation modelling methodologies but recently, agent-based modelling has gained popularity as another useful technique to deal with simulation problems in several disciplines. Agent-based modelling has been reviewed for this study to investigate its viability to handle this type of research problem (as discussed in the literature review section). Based on the current trends in the area of simulation methodology, it is important to select a method that provide advanced opportunities that are beneficial to finding solution to the research problem and evolve with the current technology. This is a quality, which has been found useful in the agent-based simulation modelling method.

3.4.1 Development of Agent-Based Model

According to North and Macal (2011) agent-based development framework comprises of three phases. Phase 1 is the development of preliminary conceptual model through problem source analysis and synthesis. The result of which is documented using flow diagrams. Phase 2 is the development of an actual agent-based model. Developing the model means translating the conceptual synthesis into a computer code, where agents are set up, agent attributes and procedures are defined. The final phase 3 is where the developed agent-based model is verified and tested. Iterative programmatic testing is carried out to test codes for errors and exploratory analysis of simulated data is done for parameter sweep and individual agent time series. There are also steps to performing agent-based modelling. First, a prototype is converted into model architectural design, which helps to understand the physical build up or structure of the concept before designing the actual agent and corresponding agent rule. Agent and agent rule design are placed in an agent-based environment where the implementation takes place. After implementation, verification and validation of the developed model are then used to check the viability of the model and its data (North and Macal 2011).

The manufacturing systems comprised of agents that exist within this system environment. ABM is a suitable approach to model the behaviours of these individual agents in this so-called 'multi-agents' environment' (because of multiple agents involved). It is an environment where agents engage in strategic behaviour and anticipate other agents' reactions when making decisions. ABM is also applicable in this problem because the past (previous customer order) is not a predictor of the future (next customer order) changing requirements.

3.4.2 Adoption of Agent-Based Model Simulation

It is widely known that solving manufacturing scheduling system related problem is a complex task, with numbers of large-scale operational uncertainties. In most cases, the complexity makes it difficult to apply traditional modelling techniques. Agent-based manufacturing system technique is one good choice and has recently been receiving a lot of attention in industry and academia (Botti and Giret 2008). One of the preferences for ABM is its capability to handle complexity associated with problem domain in an easy manner. In a multi agent-based modelling, an agent has been described as an autonomous and flexible computational system, which can act in an environment. Agents possess behaviour and attributes able to interact with other agents. They can learn from their environment, react to a change and are proactive in nature. These possibilities made ABM a good selection to consider for the current problem domain. The manufacturing facility under consideration is the type that involves dynamic processes, real-time events and changing requirements. This feature attracts ABM in a way to model how the system works rather than what should be done. The learning ability incorporated in the ABM approach means it is dynamic, able to think and understand the next or future actions without necessarily acting on the previous reaction. In this study, the ABM model is built to enhance the solution approach in this study by scheduling and allocating orders and rescheduling orders under disruption.

The ABM development process is carried out through negotiation, collaboration and communication among different agent types identified in the system. There are three agent types identified including the agent environment, they are: order agent, machine agent, and operator agent. These agents are connected as shown in Figure 3.4.
Based on the research problem requirements; the developed ABM model is expected to achieve the following functions highlighted below:

- To accept input parameters such as the order information (type, sequence, quantity, due date), machine information (number, process, setup time, process time), operator information (skills, number, availability) there are required for processing orders in the flow shop manufacturing system setting with minimal idle or waiting time, high utilisation and satisfies all constraints including the delivery due times of product orders.
- To assign and schedule required order operation to specified system resources i.e. machine and operator based on the pre-defined assignment plans.
- To improve the utilisation of each of the manufacturing system resource.
- To identify disruption and create support for shortages.

- To identify available processing gap created by disruption.
- To share information within the integrated system units.

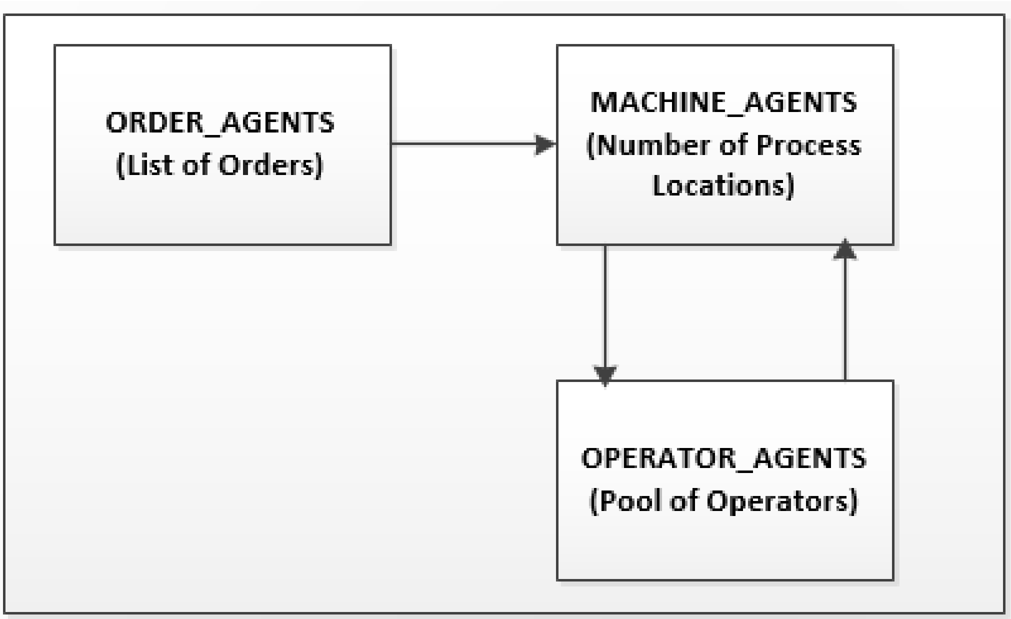


Figure 3-4: Agent Connection.

To achieve these highlighted functions, lists of individual orders under order agent type is related with machine process location representing a machine agent type, which in turn is related in a two-way direction with pool of operators as operator agent type. These relationships of agents are therefore based on their rules and conditions.

3.4.3: Agent-Based Rules and Conditions

In Figure 3.5, the learning ability of an agent in making decision for an action is demonstrated using the truth table. Two of the three agents considered in this study, order and machine agents has been matched to determine the decision-making sequence of individual agents.

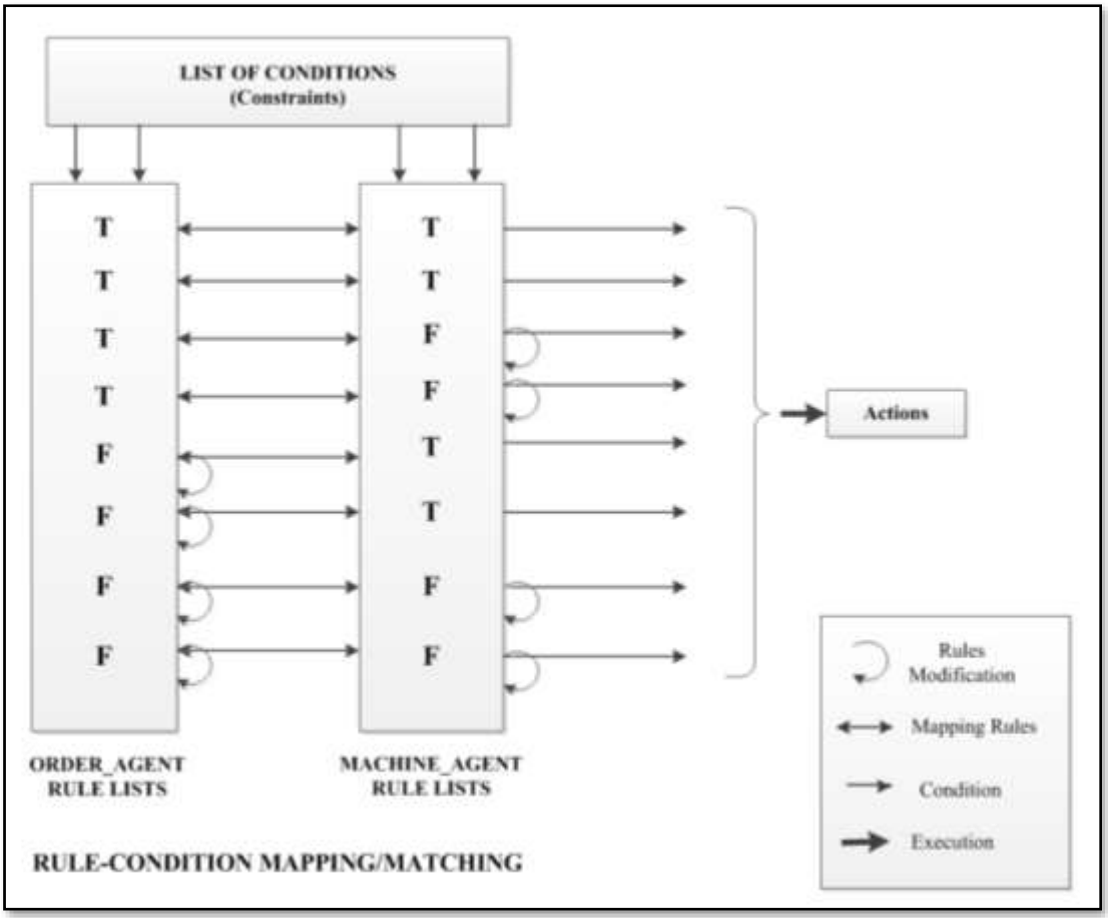


Figure 3-5: Agent Rule-Condition Mapping.

In their typical environment, there are sets of conditions constraining agent actions. These conditions all need to be true ‘T’ before any action can be taken. In both agents’ truth table lists, an ‘F’ needs to undergo rule modification for a ‘T’ condition before action is executed. These rule modification follows series of steps an agent need to satisfy to be true for the set conditions. This concept has been applied through the agent VBA coding (details in appendix) to match orders to machines based on conditional requirements, and further to allocated operators to machines on the production flow shop. Through this concept, production process is started when all rules and conditions match either directly or through rule modification. An order agent is delayed or waiting for available machine until both order-machine conditions are all satisfied. An operator waits to be allocated to machine until machine-operator conditions are all satisfied.

The agent rules and conditions are held and controlled within the agent-based environment. In Figure 3.6, the environment-rule-agent framework was designed to represent how agent rules and conditions are been controlled within the agent-based environment.

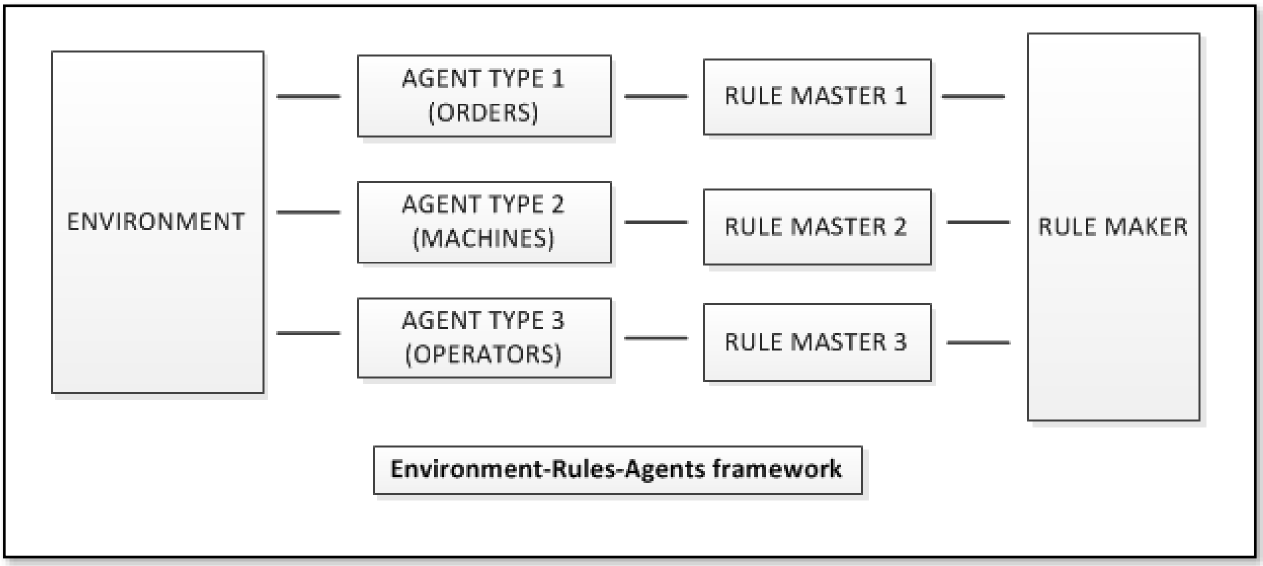


Figure 3-6: Environment-Rule-Agent framework.

In the environment, each agent types have a rule master corresponding to their agent type and a rule maker where these rules are created. The structural design of agent-based system such as the modelling architecture is used to describe this concept in section 3. 4 below.

3.4.4 Agent Based Modelling Architecture

In this section, the agent-based modelling architecture is described. To visually translate the interaction of selected agents within the ABM environment, a new agent called flow shop agent was introduced to represent the environment where agents interact as shown in Figure 3.7.

In this ABM architectural model, customer order was received and translated into order agent, which was then passed on to the flow shop agent (agent environment). Through the flow-shop agent, several machine and operator agents worked collaboratively to be allocated to order agents while the flow shop agent provides the information for order processing operations. The order production is started based on the process plan and schedule which is allied to order agent through the flow shop agent. The next sub-section discusses details of each of the agent information and their connectivity in the ABM system.

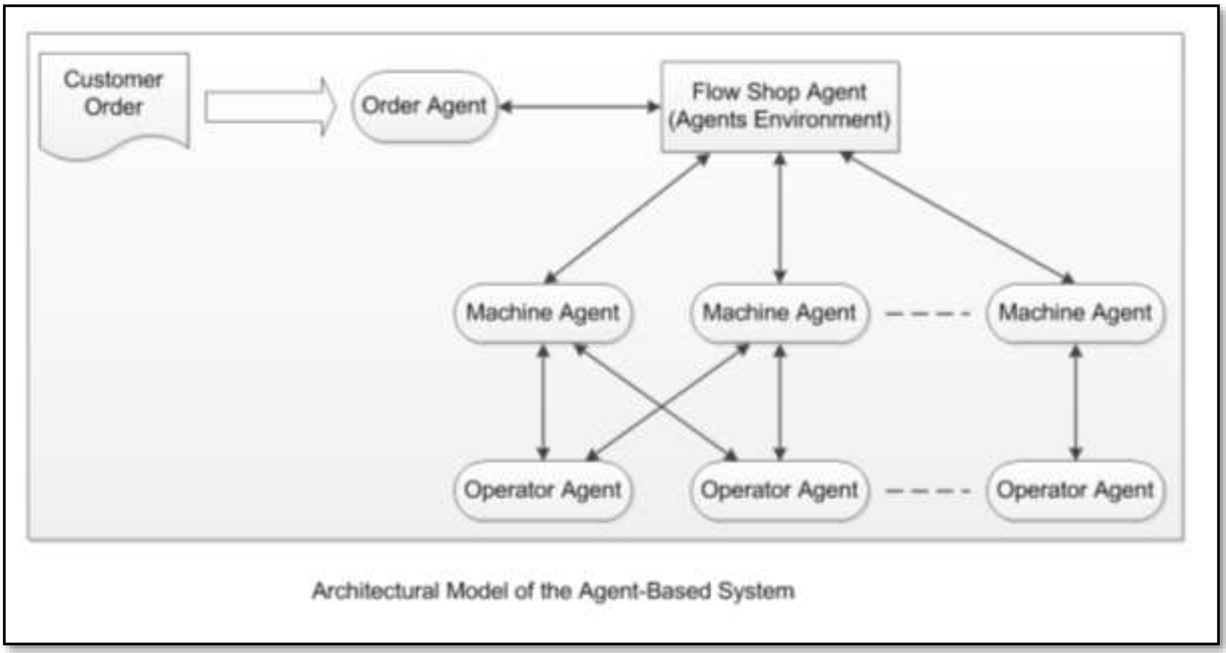


Figure 3-7: Architectural Model of the Agent-Based System.

Order Agent: The order agent receives customer orders in form of part types and then splits these order types into sequence of operations. Each split consisting of units (quantity) of order types in the pre-determined production sequence. Each order agent holds the information regarding its specific customer order including order arrival time, order quantity, split, due date, due time, and order sequence of operation. The order operation route is given to the flow shop agent controller in order to provide scheduled order processes which is generated by the interaction among machine agents and operator agents, before send back to order agent. The order agent received back the plan and schedule of order operation including allocated resources (machines and operators) according to the order requirement specifications.

Flow Shop Agent (Agent Environment): The flow shop agent acts as a controller in the manufacturing system. It holds the process rules for order operations and allocates machine agents to order and operator agents to machine agents. Basically, the mechanism of machine and operator allocation and order scheduling is conducted within the flow shop agent. According the pre-defined sequence of operation of order processing, the system adaptation to any form of disruptions is based on the proposed algorithm in this study.

Machine Agent: On the flow shop, individual machine is represented by a machine agent with information such as;

- Machine capacity,
- Setup time for each order processing
- Type of order which can be processed
- Machining time for each order type
- Processed order information
- Operator engagement information

After receiving order information from the flow shop agent, the machine agent considers the information whether it is able to process the order with the allocated operator. If there is a good match for both machine and operator on order, the order goes straight into processing or placed on a queue if machine or operator is currently busy.

Operator Agent: Each operator agent represents operator in the pool of operators in the manufacturing production cycle. Operators are allocated to machine based on their availability for the job, and skillset.
In Section 3.4.5, the architectural model goes further with the inclusion of inventory storage and rules strategy proposed in this study.

3.4.5 Agent-Based System Interaction.

The information flow in order processing using the inventory storage method and the rules application (Heuristic algorithm) in the proposed system is represented in Figure 3.8.

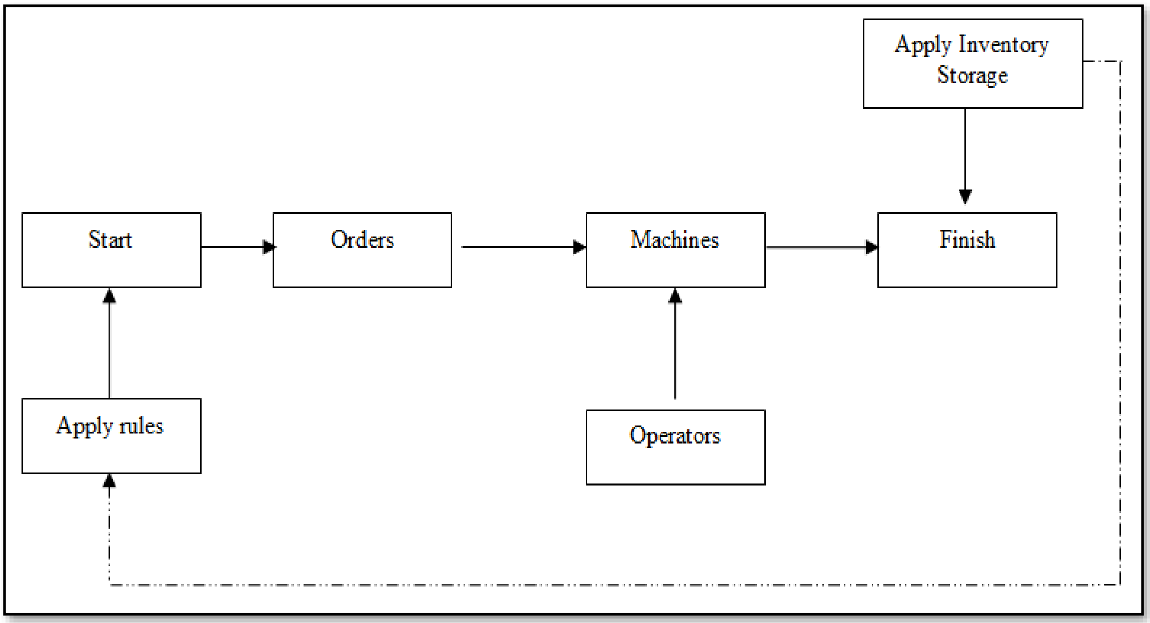


Figure 3-8: Proposed System Interaction.

When the production cycle starts, the order processing location is at the machine station. This is where orders and operators tend towards as indicated with the arrows. Orders are processed and finished at the machine station. The inventory storage was included in the flow illustrating the need for the proposed concept of shortage order borrowing. Also, the rules application is involved to guide the order borrowing process and ensure replenishment of borrowed orders through a daily adaptation. The rules application can achieve through feedback process per production cycle.

The agent-based simulation approach makes it easier for information sharing for a steady flow process through its messaging system. This messaging system of agent-based simulation is discussed in the next Section 3.4.6.

3.4.6 Agent-Based Messaging System

The idea of the messaging sequence within the agent-based environment in this study is obtained from Pan et al. (2009) where the idea was implemented in the supply chain industry for the SC entities which represent interactive ability of individual agents.

The messaging sequence concept is therefore adopted in the agent-based simulation represented in Figure 3.9 for the three agents including the customer, production floor and process. In the UML sequence diagram presented, the type of inter-relationship and message exchange among the system agents is shown. This enables order processing through messages such as; order request, resources allocation, order production and dispatch information that are being sent within the system.

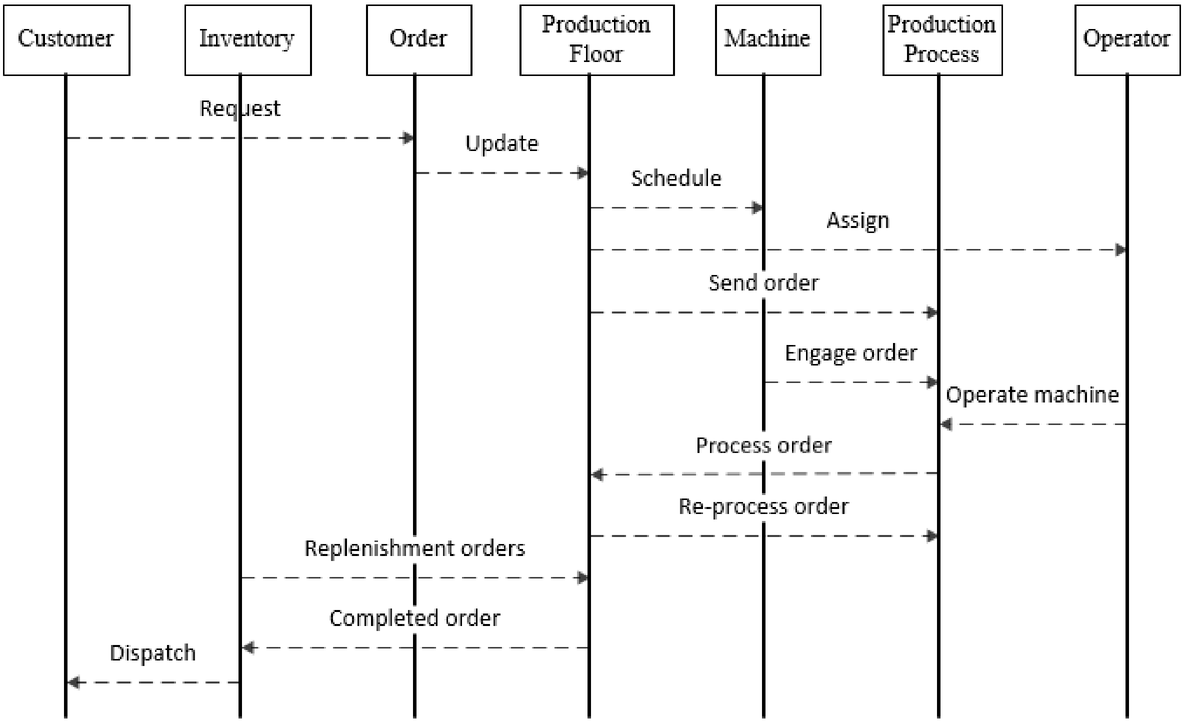


Figure 3-9: The System Message sequence diagram.

The customer sends an order request, which is updated on the production floor. Upon receipt of the customer order request, the production floor schedule machines based on the order information. The order and machine schedule are used to assign operators on the production job. As a result, a machine been allocated to an operator engages the order for production processes. The production processes occur in a loop (denoted by the re-process order) of operation until all assigned order has all been completed. In which case, the completed order information is passed on to production floor for order dispatch to the customer according to the request. A visualisation of the ABM concept is depicted in Figure 3.10.

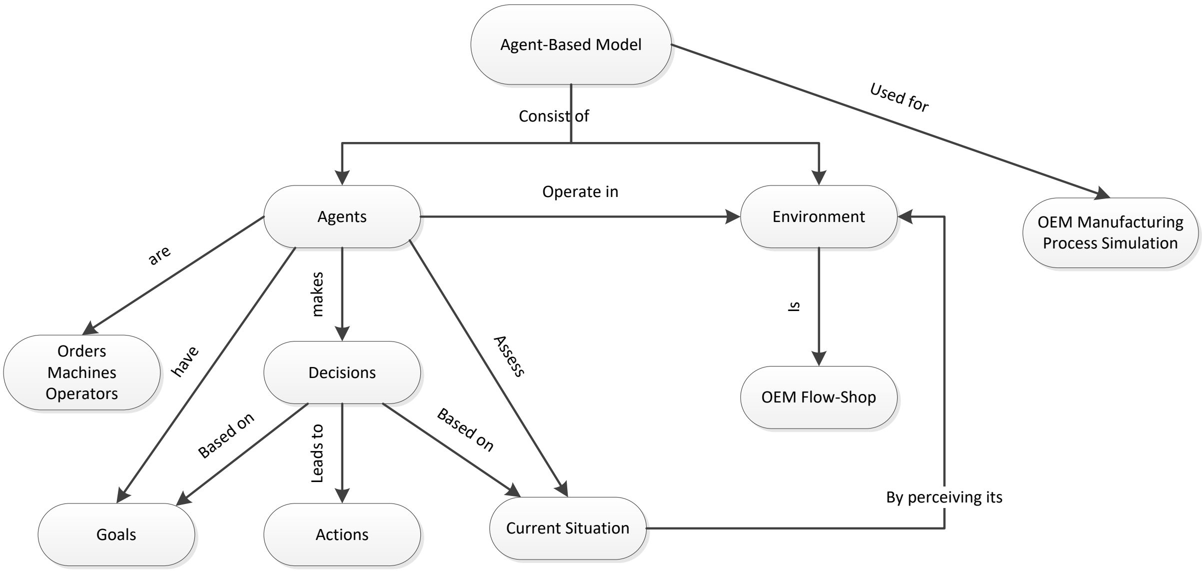


Figure 3-10: A simple ABM visualisation.

The overall concept of the knowledge about ABM approach for the current problem can be visualised using Figure 3.10 adopted from Hall and Virrantaus (2016), showing a simple conceptual map of ABM relationships.

3.4.7 State Transition Representation for ABM

Another example of UML diagram adopted for illustrating a system entity status is the state transition. It is an interaction diagram useful in capturing the notion of an agent process (Pan et al. 2009). The transition diagram involves three elements, which include nodes that depicts the states, the decisions that determine the next state transition depending on the environment, and the arrows between the nodes, sometimes nodes and decisions showing all the events and processes that can cause transitions from one state to the other. The diagram is used to represent the dynamics of the agents in the system, and especially, the flow between system elements. It considers the different states of agents and how they transit through action (as discussed in Section 3.5.3 above). It basically represents agents' behaviours, and agents react to actions in the system environment. The state transition chart of the three main agents of the system is illustrated below in Figure 3.11.

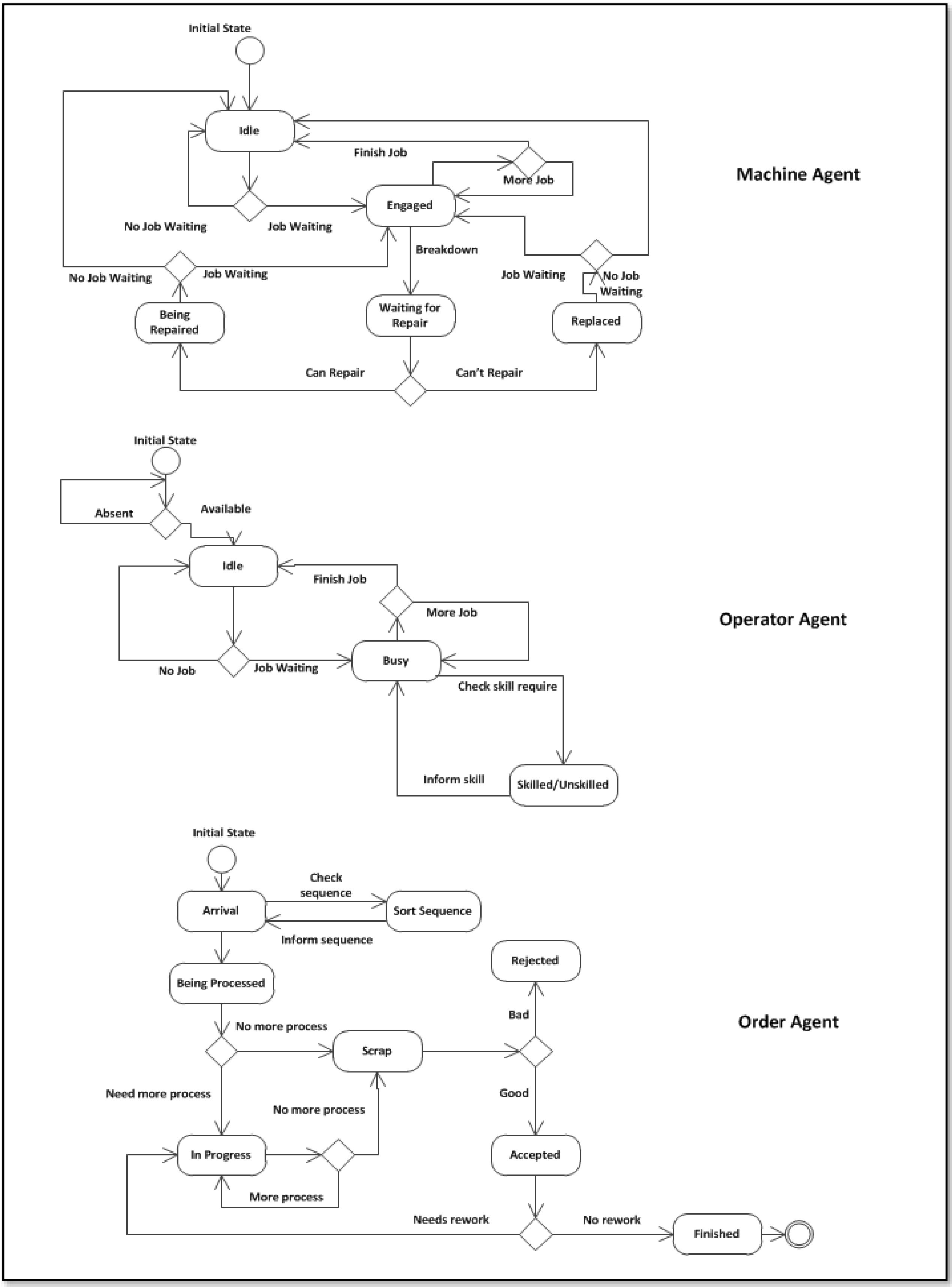


Figure 3-11: State chart model of the system agent.

3.4.7.1 State chart model of machine agent.

The initial state is the idle state. When there is no job waiting, the machine remains idle but get engaged immediately when there is a job waiting. Machine agent is in engaged state when it's performing order processing operation. In this engaged state, three events can occur. The machine agent can finish the job and start another immediately. It can finish job and return to idle if there is no more job waiting. Also, it can experience breakdown in the process (the state which is out of scope of this study). When the machine breaks down, it's in waiting for repair state. The machine can either be repairable or not. The state changes to being repaired if the decision is repairable or changes to replaced, if the decision is not repairable. At both replaced and being repaired states, the machine agent state transition into either engaged, if there are jobs waiting, or idle, if there is no job at the time.

3.4.7.2 State chart model of operator agent.

At the initial state, an operator can be absent or available. If available, operator agent becomes idle and remains idle until there is a waiting job. There occurs a transition from idle to busy when a job is waiting and remain busy until the job is finished or no more job is waiting. Meanwhile, at the busy state, an operator agent's skill is determined suitable for the waiting job.

3.4.7.3 State chart model of order agent.

Arrival of order demand from customer starts the transition of order agent. At this state, order is checked and informed of schedule and sequences of production and delivery. An order agent transition changes to being processed immediately it engages with machine and operator. In the case that there are more processes needed, the transition becomes work in progress.
The state transition diagram models the behaviour of individual agents. It is however important to reaffirm that the individual agent actions are partly determined by other agents' states and the environment in which they exist.

The state transition of each agent is shown in Figure 3.12 in form of the flow of order production. Its diagram is used to demonstrate the input-process-output operation and encapsulates the various action and interactive relationships that exist during the order production.

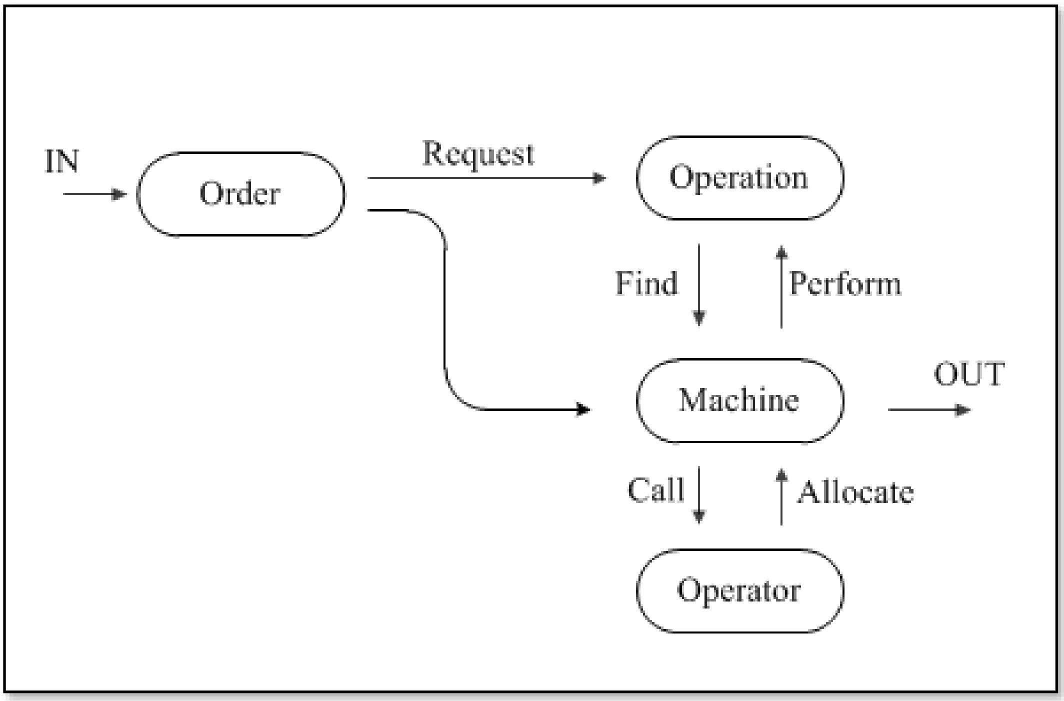


Figure 3-12: Flow of order production.

An order got into the system to request operation. For an order to be operated upon, it seeks a machine location where this operation can be performed. Operation finds a suitable machine. The machine is matched with the operation and performs the requested order operation. Before performing the order operation, the machine calls for an operator available and skills. The suitable operator is matched and got allocated to the machine for the initially requested order operation, after which the order production is completed and is out of the system.

The process described in Figure 3.13 was then used to modify the initial IPO model of the system. The new IPO model that is more specific to the developed ABM system is illustrated in Figure 3.13.

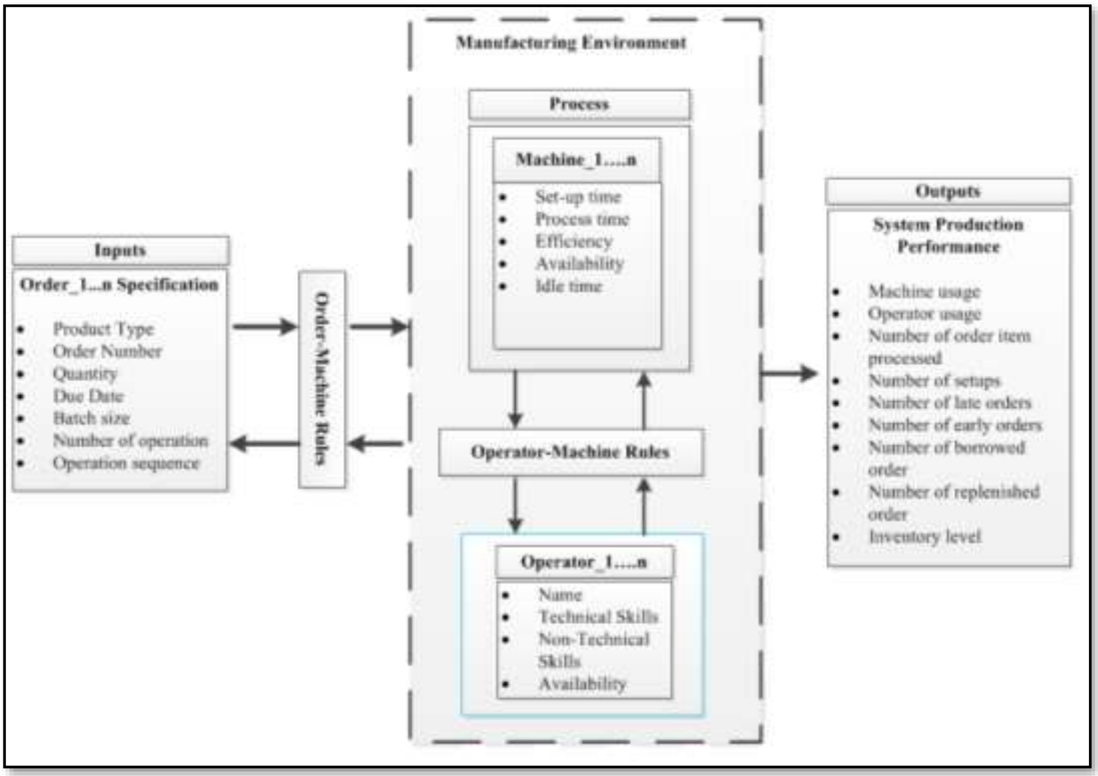


Figure 3-13: ABM Specific IPO-Model.

The inputs which consist of n number of order requests and their specifications are therefore matched with order-machine rules through the agent-based simulation development paradigm. This works in the same way for operator-machine rules, which matches the operator with machine, with their characteristic parameters. The output of the system generates production performance listed in the key performance indicators. But specifically, the number of setups; borrowed orders; completed orders; replenished orders etc. are the most significant to the analytical performance of the proposed system.

The agent-based simulation model was created with the integration modules (inventory and heuristic optimisation) for the purpose of achieving the research goal. The significance of the inventory module of the system is discussed in the next section.

3.5 Inventory Module

The concept implemented for the inventory module was adapted based on the investigation of related studies. In the manufacturing industry, Moinzadeh & Aggrawal, (1997) and Paul et al. (2014) utilised inventory replenishment strategy in finding solution to the problem of production disruption. The same idea has been used in the supply chain industry by Snyder et al. (2012), and forms part of the integrated units for the current research problem resolution.

The inventory module is one of the components of the proposed framework through which the inventory replenishment strategy is applied. The effect of the flow shop production disruption on inventory storage cannot be overemphasised. When the requirement of customer order demand goes contrary to the planned schedule and causes disruptions, controlling the inventory storage becomes challenging. Based on uncertainties associated with customer’s assembly line, disruption erupts on manufacturing flow shop. In this study, simulation-based inventory replenishment strategy is explored for managing inventory and production processes in manufacturing systems. Through simulation experimentation, the system behaviour can be understood before and after implementing the proposed inventory replenishment strategy and examine the impact. Although the control of inventory particularly in supply chain has been addressed in literatures such as Cetinkaya and Lee (2000), the problem and strategy in this work has not received adequate attention previously. Precisely, this work considers instances of random changes in sequence of demands from customers. Ideally, these customers’ demands should be produced on the manufacturing flow shop according to the changes and delivered as such. However, the effect of random changes disrupts planned production schedule, causing production backlogs. And so, manufacturer’s inventory holding policy is in disarray. Manufacturer is expected to hold economic level of demand quantity, but the result of disruption on the flow shop means the inventory requirement policy of the manufacturer is dictated by the effect of customer’s changing requirements (disruptions) that push production on the flow shop.

The proposed strategy focuses on satisfying customer changing requirements at the face of disruption through inventory support and replenishing the inventory through strategic replenishment scheduling on the flow shop. The idea relates to non-instantaneous replenishment referred to in Chang et al. (2010); Soni (2013); and Wu et al. (2006). Non-instantaneous Replenishment occurs when production is not instantaneous, and inventory is replenished gradually, rather than in lots. The three papers discuss optimal replenishment policies for non-instantaneous deteriorating items. In Chang et al. (2010) the focus is on stock- dependent demand. In Soni (2013) price and stock sensitive demand under permissible delay in payment is emphasised while Wu et al. (2006) based their study on stock-dependent demand and partial backlogging.

In this study, the optimal inventory replenishment strategy is presented for non-instantaneous non-deteriorating items with demand changing requirements in terms of sequence, due date and order cancellation. The chart below in Figure 3.14 cites an example of three order types in inventory. Each order item in inventory is expected to support customer demand satisfaction.

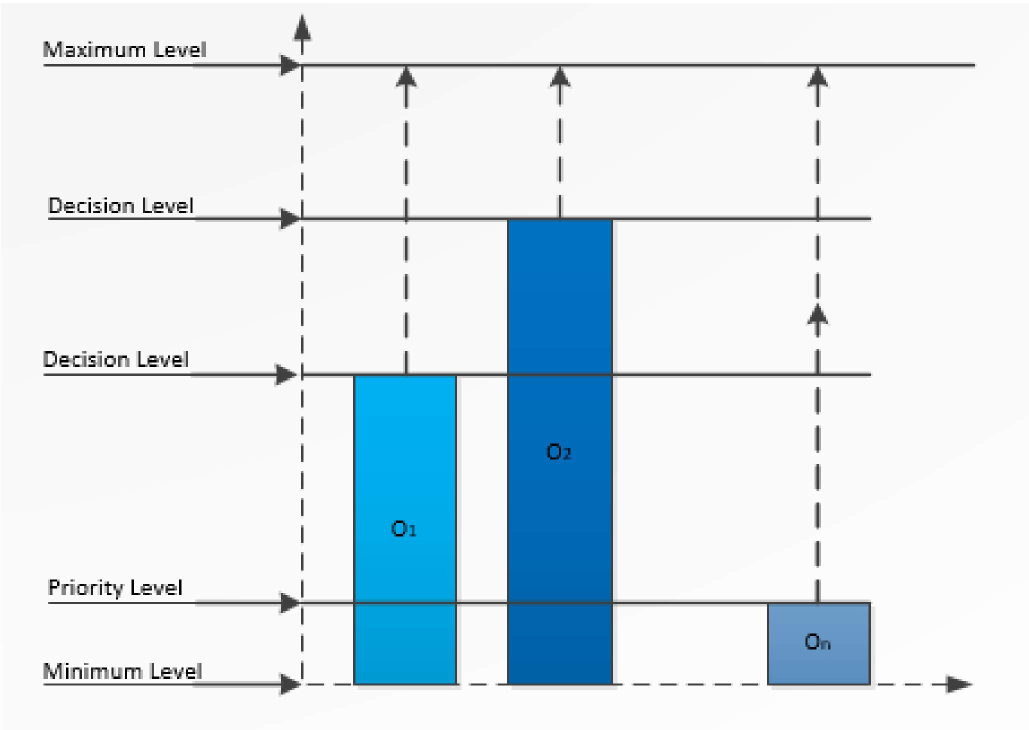


Figure 3-14: Replenishment strategy graph.

As shown in the chart in Figure 3.14, all order types have minimum and maximum inventory level. Inventory level of any order type becomes critical when it goes beyond the minimum level and over-stocked above maximum level. For example, the figure shows inventory of orders {O_1, O_2, to O_n} as an indication of inventory that have been used to satisfy flow-shop shortages and needs replenishment. To ensure adequate and non-biased replenishment, the proposed heuristic (discussed in Section 3.6) is developed. The heuristics works by giving priority to the least order in the inventory at the time of replenishment, as indicated by the 'Priority Level'. Also, the heuristic help make decision when two or more inventory levels are average and compete for replenishment. The term 'Decision Level' means the inventory level at which the heuristic would make decision which inventory to replenish at the time of replenishment. The replenishment rules are also based on conditions such as order current level flow shop ‘available time’ as detailed in the proposed heuristic. The proposed heuristic and the inventory replenishment strategy are both implemented to solve the disruption problems through their incorporation with the agent-based simulation model. As a matter of illustration, the maximum inventory in this study represent inventory at 100%, those within the decision level are above 50%, where decision need to be made which order to replenish based need, time are resources availability. The priority is inventory at less than 50% while the minimum level denotes critical or zero inventory. The percentage is easily used to represent different levels of orders of different types and quantities.

The efficient use of inventory resources is particularly important for successful implementation of the proposed Production-Disruption heuristic optimisation system. Like it is in the concept of Just-In-Time (JIT) system which is widely recognised as a way of minimising inventories. In this case, the relationship between the production and inventory has been discussed in JIT literature. However, in this context of production disruption recovery, inventory as support for recovery is an unexplored area.

In other production-inventory applications, the time and holding cost are important keys for decision-making. Inventory level is kept to the optimal minimum to achieve the economic benefits. This study builds on these practical motivations concerning production-inventory systems, but the objective is to provide a model that apply inventory as support for disruption recovery through replenishment strategy. Therefore, an integrated production-disruption inventory replenishment model for OEM manufacturer is developed. A gradual sequential inventory replenishment policy is considered while customer demand delivery is considered as priority.

The effect of inventory and its replenishment comes to play when a disruption occurs. The disruption can come as cancellation of demand, changing sequence of delivery or change in the due time. When this happens, it can either stress production process causing demand shortages or create ‘available production time’ increasing resources idle time. When demand happens, the inventory is called upon to support with outstanding demands to be delivered to satisfy customer demand. In return, the inventory is replenished gradually to balance all inventory levels while considering potential need for demand shortage support.

In a typical example of three different demand types with three inventory levels, the proposed heuristic works in such a way to allow replenishment using the available time. The way in which inventory of order can be replenished would be based on their levels of inventory. The most critical level of inventory will be considered for replenishment to match the inventory level of the next available order. When there are more than one orders with the same levels of inventory, the agent-based decision-making will determine different time-slot sharing of order quantities for equal replenishment quantities where possible. This is the levels of inventory illustrated as decision level in Figure 3.14. This is to support the gradual replenishment strategy.

It is important to note that not all the three types of disruption create available time. Cancellation disruption create available time orders are cancelled which might render some machines and operators idle. Also, change in sequence disruption can create available time through time saved for machine setup. This happens when orders of the same types are re-sequence to follow each other on the production line. Therefore, the initial setup time can be saved. However, time saved from machine setup might not be counted as available time if the setup time is less than process time of a unit of order that require no setup of its own. The change in due date disruption is the one that cause delay and steal from the initial planned schedule, minimising number of order unit production.

Through the proposed framework, the change in due date disruption is handled by introducing the inventory which serve as “borrow” support for shortages. Also, the agent-based method make it possible to calculate process times that might be saved when there is cancellation disruption, hereby helping to re-sequence replenishment orders.

Agent-based model captures the production behaviour of individual order types that influence their production scheduling. These influences include the process time, machine setup time and other resources availability. The model combines different orders that requires replenishment based on their current inventory levels and production shortages, allowing trade-off decision to be made. The trade-off decision which translate to available time sharing among orders is used to gradually maintain the levels of inventory against risk of maximum production shortages.

Agent-based simulation models the behaviours and interactions of individual entities within a system, and therefore applied to capture the self-optimising behaviours of order entities with replenishment requirement. This application of agent-based model is used to assess the potential of agent-based simulation to tackle the highlighted research problem. It is also used to act as a proof-of-concept proposed in the current research.

Due to production disruption, production plan and schedule is affected, causing incomplete order production, shortages and backlogs. The affected orders are not ready for delivery in due time, in right sequence and quantities. Therefore, there is need to respond to this problem to consistently satisfy customer demand, despite disruptions. The system is developed using a concept which enables production shortages to be supported through order borrowing from inventory. However, to ensure continue support and avoid risk of critical inventory level, the inventory need to be replenished according to demand and shortages. It means the level of inventory need to be maintain consistently to achieve this objective. Through disruptions activities, the system allows 'order borrow', and obtain 'available production time'. The available production time is the means to inventory replenishment. But the question of which order to choose and by what quantity to replenish emerged. To deal with this problem, the idea of gradual inventory replenishment is explored as inspired by related problems in previous studies. To achieve this replenishment method, the 'available time' sharing is considered, where decision is made to identify which order(s) to replenish and by what quantity. The decision is made through agent-based intelligence capability using the knowledge of current levels of inventory, production rate and shortages as well as rate of demand.

3.5.1 The Inventory Replenishment Concept

To determine what order to select for replenishment and by how many, the decision is obtained from agent-based. The agent-based can provide number of order quantity that can fit into the available time. This is possible using the process time of each order quantity and the machine setup time, which are fixed for individual order types, in all cases where there are inventory levels of orders with different or same levels. In a case where there is one order with most critical level of inventory, the decision is made to determine how many quantities of that order are required to replenish for the inventory level to equal or almost equal the level of inventory of the next order. When there is more than one inventory of orders at the same levels, the decision is made by calculating how many of each order quantity will fit in the available time to equal or almost equal the level of inventory of the next order(s). The order with the most quantity is selected first, before the next until the available time is exhausted. This is the gradual replenishment method proposed to enable continuous production support through borrow, to consistently maintain inventory levels and avoid the risk of critical inventory level.

In Figure 3.15, the inventory behaviour as a result of disruption and replenishment is represented.

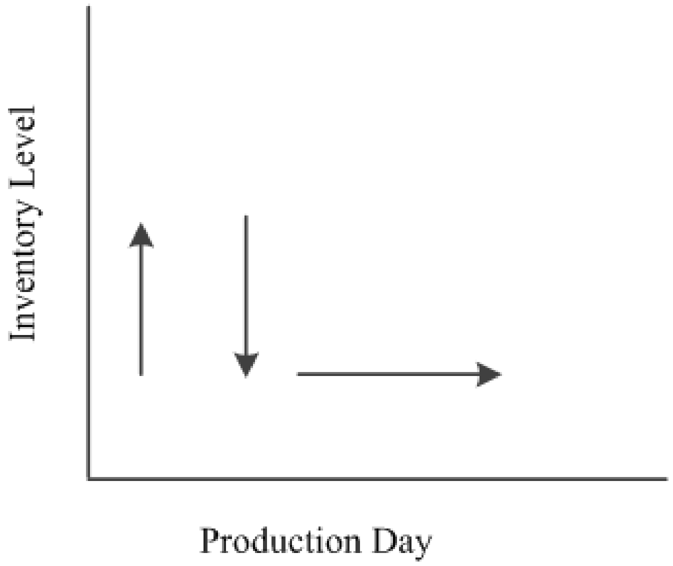


Figure 3-15: Inventory Behavioural Graph.

The inventory can go up when borrowed orders are being replenished. The inventory level can go down when inventory items are been used to support production shortages caused by disruptions. The inventory level can remain unchanged when no order is borrowed or replenished.

3.5.2 Inventory Replenishment Cases

In practice, Figure 3.16 presents the inventory levels replenishment cases that is employed in this study.

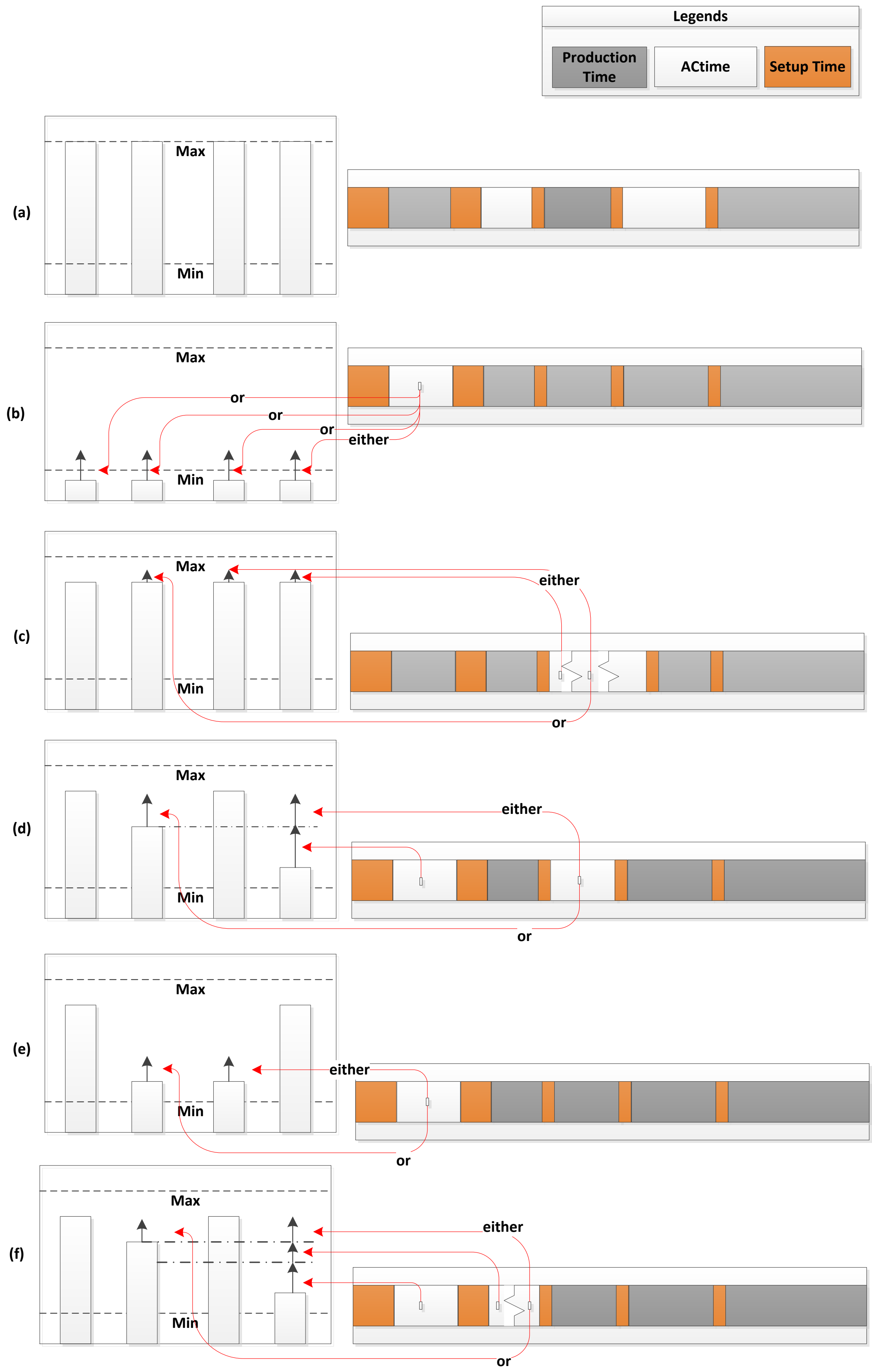


Figure 3-16: Inventory Replenishment Cases.

For the proposed inventory replenishment strategy in this study, the replenishment cases are represented in Figure 3.16 (a-f). The cases demonstrate the heuristic approach for gradual inventory replenishment strategy. The gradual replenishment strategy is employed in this study because of the nature of the order and the research problem. The gradual replenishment is significant in order not to focus on one order replenishment when others need equal attention. Also, it is necessary to replenish gradually rather than focusing on specific order to prevent keeping unnecessary inventory while other order inventory levels are at risk. The replenishment is made possible through the available time created due to customer disruption such as order cancellation. In Figures 3.16 (a-f), for each inventory levels, maximum and minimum inventory levels are shown and the corresponding charts for current available time (AC_{time}) alongside the process and setup times. The current available times are utilised through production rescheduling of replenishment orders. Each figure shows different inventory levels and how the gradual replenishment strategy is performed.

In case (a), all order inventory levels are full. This means there is no order borrow or/and no replenishment is required even when there is available time. In this case, the available time is considered idle resulting to low utilisation of production resources. Case (b) shows a situation where all order inventory levels are at critical levels and at high risk of customer order demand shortages. Using the arrows to represent the levels of each replenishment attempts through the current available time, it shows the gradual replenishment of each levels based on the proposed strategy. The strategy used is called the Min-Max strategy whereby the minimum order production quantity is selected from all maximum production quantity that can fit within the current available time for processing. This means the selected inventory is replenished to the level where others can level up within any given available time. The process continues to select minimum quantities from maximum where two or more order inventory levels are the same. The current available time in case (b) can be utilised for any of the order inventory levels that is selected through min-max strategy. The same situation occurs in case (c) where all order inventory levels are equal but at safe levels. However, judging by the level of each order inventory levels which need very low quantities of order replenishment to hit the maximum inventory levels. A situation can occur where the same available time can be shared for more than one order replenishment. This is dependent on the order quantity decided through the min-max strategy. In case (d), one of the order inventory level is the least. In this situation, the least order inventory level is selected for the given available time for replenishment to be less or equal to the next order inventory level, as indicated by the arrow. After the first replenishment attempt, the situation becomes the case of two orders having the same inventory levels. This is the case where the min-max strategy is applied to select the minimum quantity of the maximum possible to replenish with the next available time, as it is the case in case (b) and (c). In case (e), two orders are on the same inventory levels. Using the min-max strategy, it can be decided either one or the other order inventory level will utilise the current available time.

The situation in case (f) is where one order is least and in different level with the next least inventory level. Considering a limited current available time for the least inventory level replenishment, the available time is exhausted and not enough for the selected least inventory to level up to the next inventory level. And so, part of the next available time is utilised to the same order inventory in order to level up with the next order inventory. At the same levels, the remaining shared current available time can be utilised by any of the two order inventory as decided using the min-max strategy. The min-max strategy and the time-sharing ability is made possible through the agent-based capability of making decision and information sharing.

The proposed strategy attempts to utilise all current available times to maximise the number of order quantities, maximum resource utilisation while inventory levels are gradually replenished to avoid unnecessary order inventory. Order inventory replenishment continues using the time-sharing and the min-max strategy until all order are full or all available time is exhausted, whichever comes first.

3. 6 Heuristic Rules Development

The development of the heuristic algorithm is for the optimal maintenance of the inventory level of all order types involved in production. The maintenance of the inventory is a process that establishes the optimal level of inventory to hold and maintain in order to meet expected service levels for satisfying customer demand. The proposed inventory replenishment strategy with the heuristic algorithm offers a technique for synchronising inventory and production decisions. The strategy is related to manufacturing system finished product inventory level. It is the case of manufacturing system receiving different order demand types from customers. Ideally, manufacturing facility is expected to process order as they are received and schedule these orders based on the flow shop resources. They are also expected to maintain corresponding inventory level for all order types. A functional inventory policy is expected to guide against order stock-out as well as over-stocking.

The proposed heuristic algorithm in this study is applied to help replenish the inventory after it has been used to support production due to disruptions. The algorithm which is integrated in Agent-Based simulation form part of inventory replenishment strategy experimented in this study. This is developed for flow shop order processing in a parallel machines' environment with multiple orders processing, taking into consideration inventory storage replenishment in the face of production disruption based on customer changing requirements.

The heuristic focuses on determining shortage orders, borrowing orders, rescheduling borrowed order for inventory replenishment. The replenishment process is done gradually using the extended replenishment strategy adopted from the works by Chang et al. (2010); Soni (2013); and Wu et al. (2006). It is assumed that the heuristic will be applied when there is any type of disruptions on the production flow shop. This is when orders need to be rescheduled for inventory replenishment. The agent-based model provides additional information for the heuristic implementation.

The development of the heuristic algorithm steps focuses on replenishing inventory based on individual order level. It takes into consideration order with lowest inventory level as priority. It considers orders of the same level, by applying replenishment based on the production schedule. From the production schedules, the heuristic considers orders before and after the available time provided by the ABM. Based in different condition, heuristic algorithm considers creating new setup where a different order type is expected to be replenished.

3.6.1 Reasons/ Justifications for Heuristic Algorithm Approach

Heuristic Algorithm has been adopted for the following reasons:

- It is a method used when process speed as well as solution quality is essential. The continuously changing requirements require a speedy response which heuristic algorithm can provide (Marti and Reinelt 2011).
- It allows prompt production scheduling adaptation based on disruption in customer daily requirements and inventory demand.

- Unlike other techniques such as GA, heuristic algorithm can accommodate requirement update into the system while the process is executing. This is not possible with GA that search for solution only per input, one at a time.

However, the more flexible characteristic of heuristic algorithm approach is important for the research problem especially in a dynamic complex production environment with 'elastic' order string.

3.6.2 Heuristic Steps

The heuristic optimisation algorithm approach is adopted to help accommodate production disruption and assist in the replenishment of borrowed orders (as discussed in the replenishment strategy). The heuristic is implemented with consideration for the inventory storage, which act as a backup for production schedule in time of disruptions. There the heuristic algorithm steps are developed based on different inventory level scenarios and flow shop available process time (discussed in the next sections). The following steps represents how the heuristic algorithm is been executed to optimise production performance in spite of disruption and order borrowing.

Heuristic notations

- n = Number of orders
- D = Order demand quantity
- ΔD = Disrupted demand quantity
- DT = Due time
- ΔDT = Disrupted due time
- S = Sequence of demand
- ΔS = Disrupted sequence of demand
- I = Inventory quantity
- P = Production
- B = Borrow quantity from inventory
- U = Unsatisfied order demand
- SD = Satisfied order demand (This includes type & quantity of an order)
- SO = Shortage
- R = Replenishment quantity
- $R_{min(max)}$ = The minimum of the maximum number of replenishment quantity
- N = current day
- N+1 = Next day
- ABM = Agent-Based Model
- AT_{time} = Total available time
- AC_{time} = Current available time being allocated

- M_{setup}= Machine setup
- P_{time} = Process time
- PP = Production period

Step 1: Obtain D, DT, S, I, and PP.

Step 2: Sort S processing based on order modelling rules

Step 3: Schedule D in S of DT for N

Step 4: Re-schedule if ∆D, ∆S, and/or ∆DT for N

Step 5: For P ≤ (D or ∆D)

- If P = (D or ∆D), then SD

- Else if P < (D or ∆D), then SO end if.

Step 6: For SO, Borrow B from I, where B = (D or ∆D) - P

- If P+B = (D or ∆D), then SD ➔ SO = 0 where I > 0

- Else if P+B < (D or ∆D), then U ➔ SO > 0 where I ≤ 0 end if.

Step 7: Assess ABM time-sharing decision.

Step 7.1: Obtain AC_{time} each of AT_{time} (where $\sum AC_{time} = AT_{time}$) from the ABM time-sharing decision.

Step 8: For I ≤ 100% and $AT_{time} \geq 0$

- If I ≤ 100% and AT_{time} = 0 then do nothing, else

- If I < 100% and AT_{time} > 0 then

Step 9: Schedule $R_{min\ (max)}$, where R > 0; $R = \sum R_{min\ (max)}$

Step 9.1: If critical or safe and different (I - B) levels for given AC_{time} then Replenish R for the least (I - B) level, until R ≤ the nearest (I – B) level(s) then goto step 9.2 if R =equal nearest I - B) level(s) else select next AC_{time} and repeat step 9.1end if.

Step 9.2: If critical or safe and same (I - B) levels for given AC_{time} then Calculate and select (I - B) level with $R_{min\ (max)}$ obtained from ABM and Replenish $R_{min(max)}$

Step 9.3 Repeat step 9.2 until no (I – B) levels are same then goto step 9.1

Step 9.4 : If $R_{min(max)}$ > 1 and = to same(I - B) levels then, Replenish $R_{min\ (max)}$ at random or for minimum P_{time} and minimum M_{setup} until ≤ the nearest (I - B) level(s) or AC_{time} = 0 or I = 100% (whichever comes first) end if, end if.

10: Update the new I level as (I-B+R)

11: Repeat 9 Until all I = 100% or/and AT_{time} = 0 or end of N production cycle (whichever comes first)

12: Display P, U, SO, SD, B, DT, S, R, and I

13: Repeat 1-12 for (N+1) until PP is completed.

3.6.3 Implementation of the Proposed Heuristics

The heuristic obtains the customer demand information such as the demand quantities (D), types in sequence (S), and due time (DT) as input, where full inventory (I) levels are assumed initially for order types. The demand type (S) is sorted for processing based on a predefined order modelling scheduling rules of the system such as the earliest due time. The demand is then scheduled daily (N) in sequence of due times. Disruption can occur in terms of cancellation, which is disrupted demand quantities (ΔD), sequence change (ΔS) or/and change in the delivery due time (ΔDT). Customer demand satisfaction is determined under either disruption or no disruption. If the production quantities (P) are equal to demand or disrupted demand quantities, then customer demand is satisfied (SD). However, in case the production quantities are less, then there are shortages (SO). When shortages occur due to disruption, orders are borrowed (B) from inventory (I) to support production, where borrowed order quantities are production shortages from demand or disrupted demand quantities ($B = (D \text{ or } \Delta D) - P$). Customer demand becomes fully satisfied if the addition of the borrow quantities with the production quantities are equal to the demand or disruption demand quantities.

In this case, shortage is nullified to zero. Meanwhile, if the addition of production and borrowed quantities are still less than the demand or disrupted demand quantities, there would be unsatisfied customer demand (U). This case would occur when inventory is less or equal to zero and not enough to cover the shortages. When order quantities are borrowed from inventory, it need replenishment quantities (R) to manage all order inventory levels to further support production of any future shortages. The inventory replenishment quantities are based on current inventory levels (I-B) of all orders. If inventory level of any order is full or less than 100% where there is no available time, then no replenishment is done. However, when inventory level is less than 100% and there is available time, the system search for and utilise available process time, if total available time (AT_{time},) is at least one. For each replenishment operation, the system uses the min-max strategy by scheduling the minimum of the maximum possible replenishment quantity ($R_{min\ (max)}$) within the given or current available time (AC_{time}) until they are all exhausted, where total available time is the addition of all possible current available time. For schedule replenishment quantities ($R_{min\ (max)}$), current available time is allocated, where replenishment is less or equal to inventory borrowed quantities.

However, replenishing inventory borrowed quantities are considered for three different conditions for either critical or safe inventory levels; if inventory levels are different, the least inventory level is considered for replenishment using the current available time until it is zero or inventory is full, whichever comes first. In the case where inventory levels are same, the least with the same levels are considered based on ($R_{min\ (max)}$) strategy, where ($R_{min\ (max)}$) order inventory is selected. When the current available time is exhausted and not enough for the ($R_{min\ (max)}$) quantity to level to the next order inventory, part of the next available time is utilised through ABM time sharing ability. The replenishment quantities are scheduled at random when same inventory levels have the same ($R_{min\ (max)}$) quantities. In all cases, the inventory is updated with replenishment quantities, giving the inventory new quantities values of (I-B+R).

To utilise all available total times at each replenishment attempt, the system search for next current available time and repeat all replenishments steps until all order inventory levels are full (100%), available total time is exhausted or daily production cycle (N) is completed (whichever comes first). The system generates and display output in terms of number of Production (P), unsatisfied orders (U), shortages (SO), satisfied demand (SD), borrowed orders (B), due time (DT), Sequence (S), replenishment quantities (R), and inventory levels (I). The entire process is repeated for the next production day and continuous until the production period is completed.

The proposed heuristic is developed to adapt to the three types of production disruption been considered in this study; change in sequence, change in due time and cancellation disruptions on the real-life manufacturing system. When any type or combination of disruptions occurs, the system through the agent-based model generates the negative effects that trigger solution strategy, the proposed heuristic accommodates and respond to the disruptions. Each time disruption occurs, the heuristic is activated to identify shortages, determine borrowed orders from inventory and re-schedule borrowed orders to replenish the inventory.

3.7 Contributions to Knowledge

This study contributes to knowledge through the development of an innovative heuristic algorithm that schedules/reschedules production plan with replenishment orders in an Original Equipment Manufacturing (OEM) flow shop manufacturing systems. The proposed approach is used to solve the identified production disruption where there is change in sequence of order, order cancellation and most especially change in delivery due time, a disruption problem which to the best knowledge of the researcher has not receive enough attention in this manner in the past. There are evidences of Agent-Based approach implemented in manufacturing problems but in this study the approach has not been utilised in such a way to reveal time variation in between production processes that is, before and after disruption.

ABM is modelled in Excel spreadsheet using VBA since MS package such as Excel is universal in industries. The developed ABM model is easily embedded in Excel spreadsheet, making it accessible within existing industrial data, making it cost effective and time saving. It is believed that complex production problems do not have to be tackled using complex methods, techniques or ideas when simple ones can do. The system presented in this study can be maintainable within industries and use by non-technical users.

Chapter 4: Flow Shop Operations Specification Modelling and User Interface Design

4.1 Introduction

In this chapter, the previous methodology chapter is extended through the presentation of the collections of related software development specification diagrams. The development of the flow shop operation system which translate into the proposed approach integrates different modules within the proposed framework (Figure 3.2) as discussed in Section 3.2). However, this chapter discusses specifically about the system architecture, agent-based attributes and behaviours, UML diagrams such as the use case, class diagram, activity diagram as well as the databased entity relation. It continues with the system information flow diagrams integrating the Agent-Based Model with the heuristic algorithm, also the information flow diagram of each agent-based model and heuristic algorithm as a single entity is represented and discussed.

In conclusion, the chapter present the developed system user interface with sheet-tab profiles developed in Excel VBA program for its dynamic nature and easy accessibility.

4.2 Flow-Shop Production System Architecture

The overall architecture of the flow-shop system depicts the relationship among flow shop agents, heuristic algorithm with the database from user interface perspective. It shows the interaction among the agent-based simulation, the simulation animation representation, the heuristic with inventory, as depicted in Figure 4.1 below.

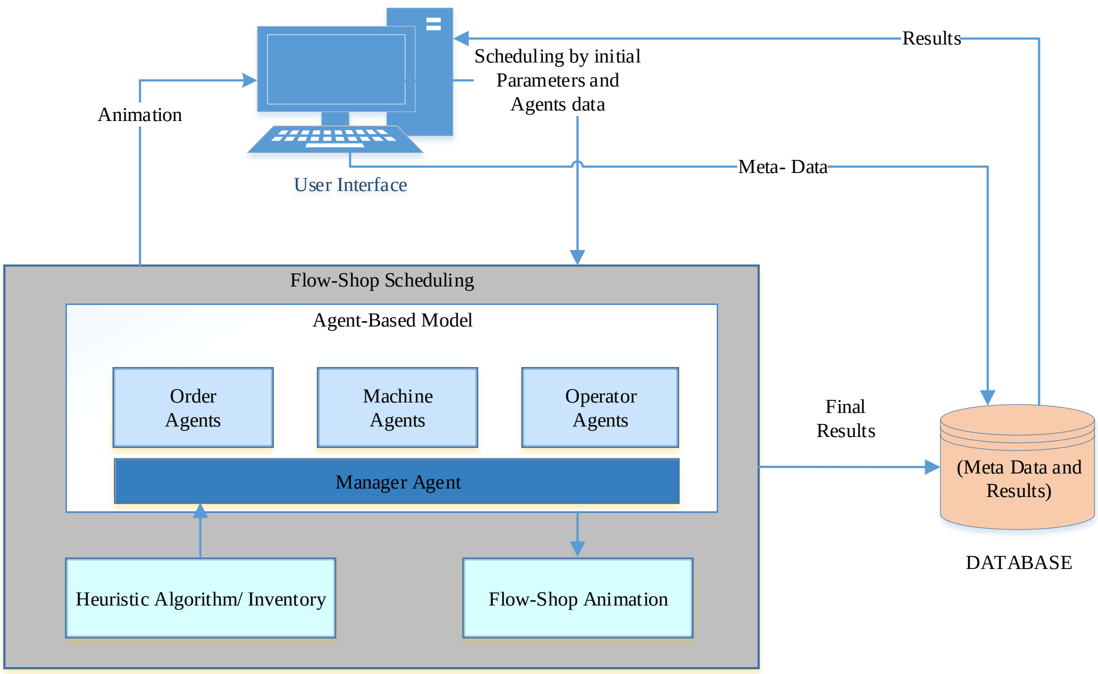


Figure 4-1: The Flow Shop production system architecture.

From the users' point of view, initial production scheduling parameters and corresponding agents' data is informed into the system through the user interface and stored as meta-data into the system database. The production input progresses from the system database as flow-shop scheduling through the agent-based simulation and heuristic with inventory approach. As the production processes occur with the simulation, visualised animation of the process is presented unto the screen of the user interface. Likewise, from the database storage, the eventual simulation results are stored and made visible in the user interface for result analysis and reporting.

This forms the basis of the developed system and the user interaction. The next section focuses on the attributes and behaviours of the individual agents within the system.

4.3 Attributes and Behaviours of Agents in Agent-Based System.

The attributes and behaviours are characteristics of agent in an agent-based simulation environment. Agent attributes are those that contain information that determines the properties of agent action, on the other hand, the behaviour of an agent depends on the role it plays within the system at a point in time. Using UML diagram concept, these attributes and behaviour can be represented for visualised understanding as presented in the next sections. However, in Table 4.1 below, the attributes and behaviours of order, machine and operator agents within the developed system are listed.

Table 4-1: Attributes and Behaviours for Order, Machine, and Operator agents

Order Agent	
Attributes	**Behaviours**
Order ID Processes (Route) Order quantities Start date End date Process start date Process end date Current process machine Current operator Queue	In process Waiting in queue Left queue Seize machine Seize operator Release machine Release operator
Machine Agent	
Attributes	**Behaviours**
Machine ID Operations (functionalities) Processing time Setup time Current order Current process Current operator Idle Idle time Busy Busy time	Process order unit Undergo setup Waiting for next job
Operator Agent	
Attributes	**Behaviours**
Operator ID Operation skills Current machine Current order Current operation Idle Idle time Busy Busy time	Operate machine Setup machine In shift

4.4 System entity relationship and UML diagrams.

From relational database viewpoint, the attributes and behaviour of agents are translated into the system entity relationship shown in Figure 4.2 and class diagram in Figure 4.3. Figure 4.2 constitutes flow shop agents' entity relationship with heuristic algorithm-inventory integration.

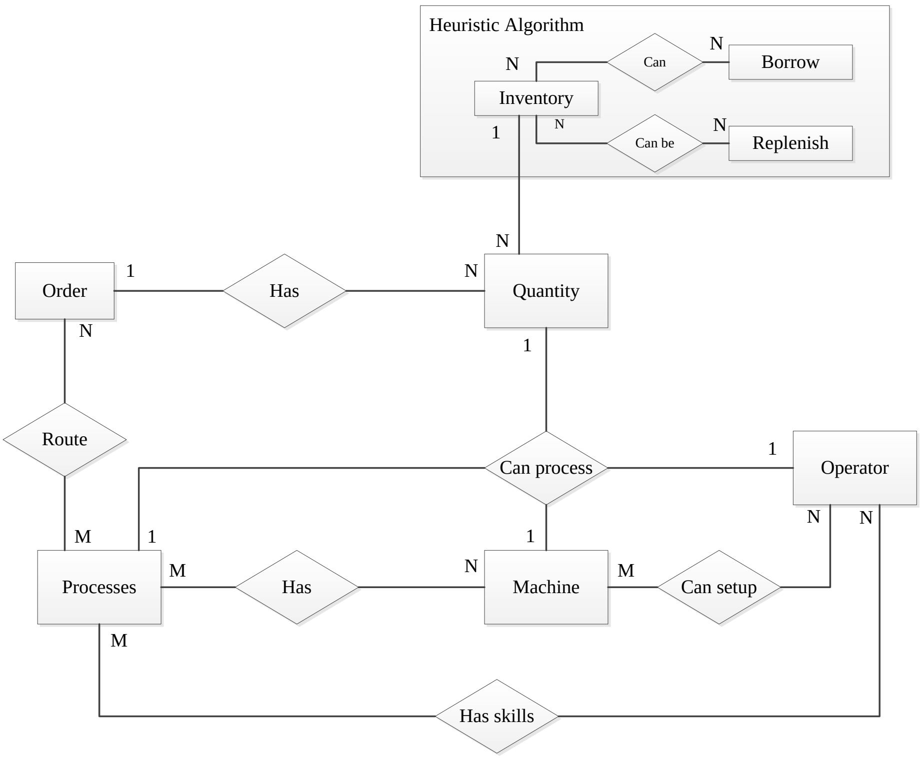


Figure 4-2: System Entity Relationship

In the system entity relationship diagram, the link and the type of relationship between each system entity is shown. An order can have predetermined number of order quantity. Number of orders follow more than one processing route. From the machine point of view, number of machines can have more than one processes and can be used to process one order quantity. Number of operators can many skills to setup and operate many machines for more than one processes. Also, from number of order inventory, a predetermined number of orders can be borrowed and replenished.

Class diagram

In object-oriented approach of software development process, class diagram (Figure 4.3) is one of the Unified Modelling Language (UML) considered highly useful in showing static structure that describes the system structure involving classes, their attributes, operations and the different objects relationships. For integrating the developed model with an existing database, class diagram is needed as a tool for relating with the database. It is considered a more robust approach rather than manually typing the modelling parameters which might be time consuming.

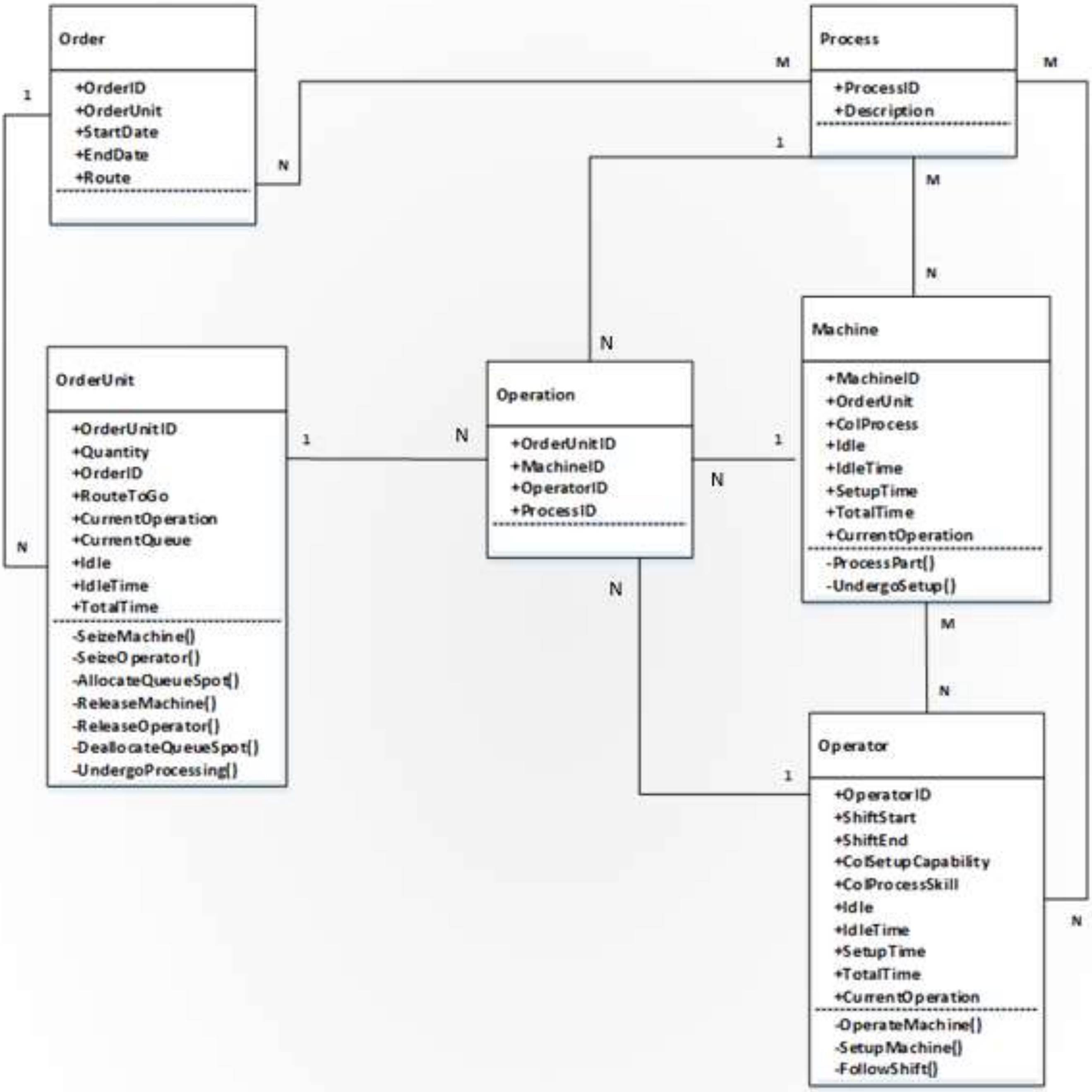


Figure 4-3: The Flow Shop agents' class diagram.

There are six major classes described in Figure 4.3, they include order class, process class, operation class, machine class, operator class and order unit class. The objects in each class comprises of class identifiers, and other attributes or properties that maps one class to the other. The identifier for order is the OrderID, ProcessID for process class, MachineID for machine class, OperatorID for operator class, OrderUnitID for order unit class and OperationID for operation class. Additionally, the mapping relationship between classes is also represented. For instance, one order can have a defined order unit (quantity), while each order unit undergoes number of operations. Many machines can have specific numbers of operator where number of operations can be performed for many order processes.

Use case diagram

Applying the UML use case diagram is essential to represent the behaviour of a user in relation to the action the user performs within the specific system environment, as shown in Figure 4.4.

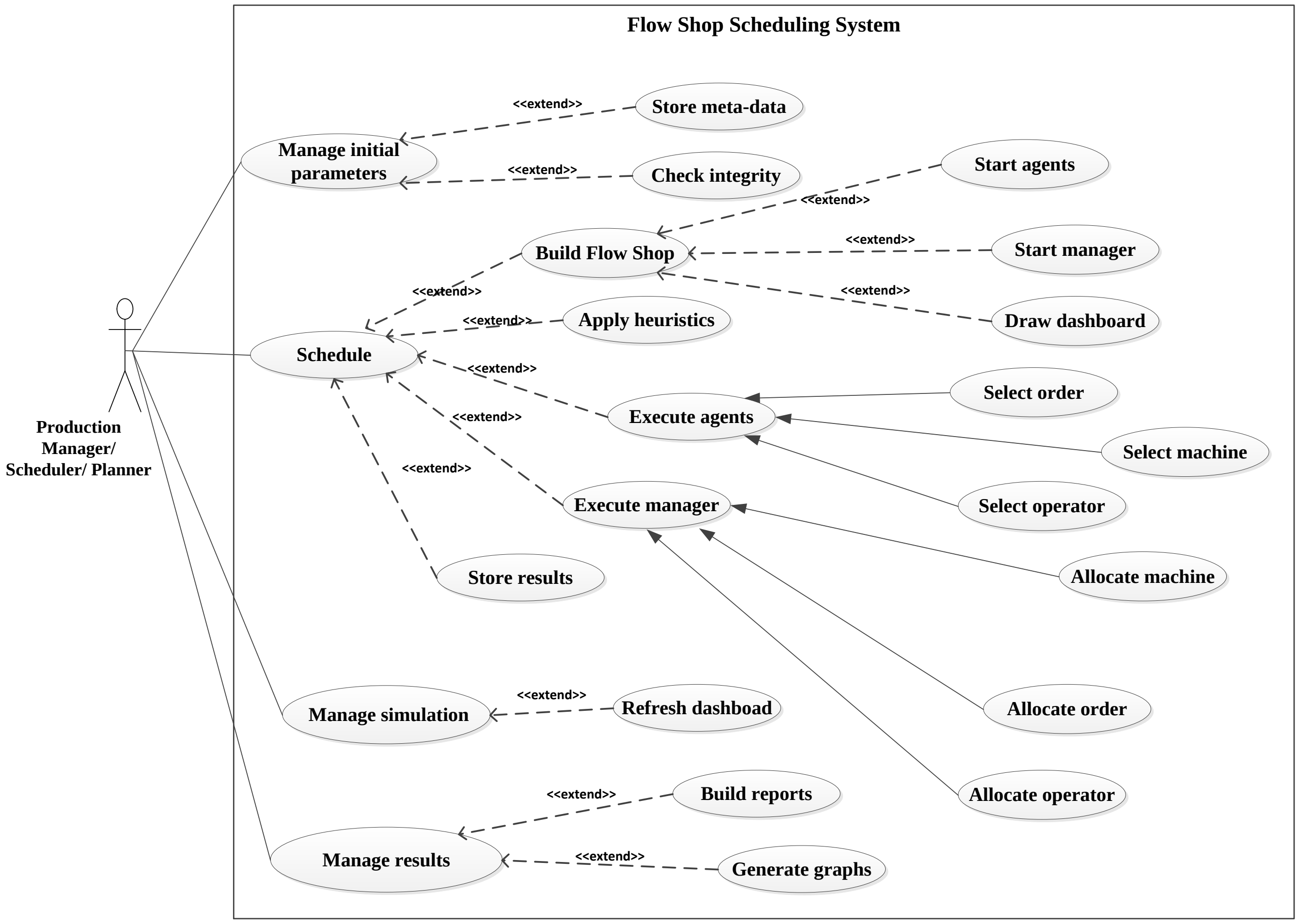


Figure 4-4: Flow shop system use case diagram.

The provided flow shop system use case shows an actor, which could be production manager, scheduler or planner and the various actions or functions they perform within the flow shop scheduling system. The actor can manage initial parameter by being able to input initial parameters while the system checks the integrity of the data before storing the meta-data. The actor can initial scheduling indirectly by setting up the requirements of the start of the scheduling process. The system commences the scheduling action while building the flow shop entities, executing the agents involved and applying heuristic where needed. The scheduling action is implemented by the system by drawing dashboard for the simulation process, starting, selecting, starting, and allocating agents according to requirements. The scheduling action ends by storing results from the outcome of the process. The actor is also able to manage simulation which the system extends to refreshing simulation dashboard. And finally, the actor is able to manage results in terms of generating graphs and developing reports.

Activity diagram

When the dynamic nature of the system is important, UML activity diagram is considered very useful. It is in form of flowchart representation of the flow of activity from one side to another within the targeted system environment. It can simply be described as the system operation in a control flow manner. Activity diagrams are developed specifically for the current study as shown in Figures 4.5- 4.8, for initial parameters, scheduling, simulation and results respectively.

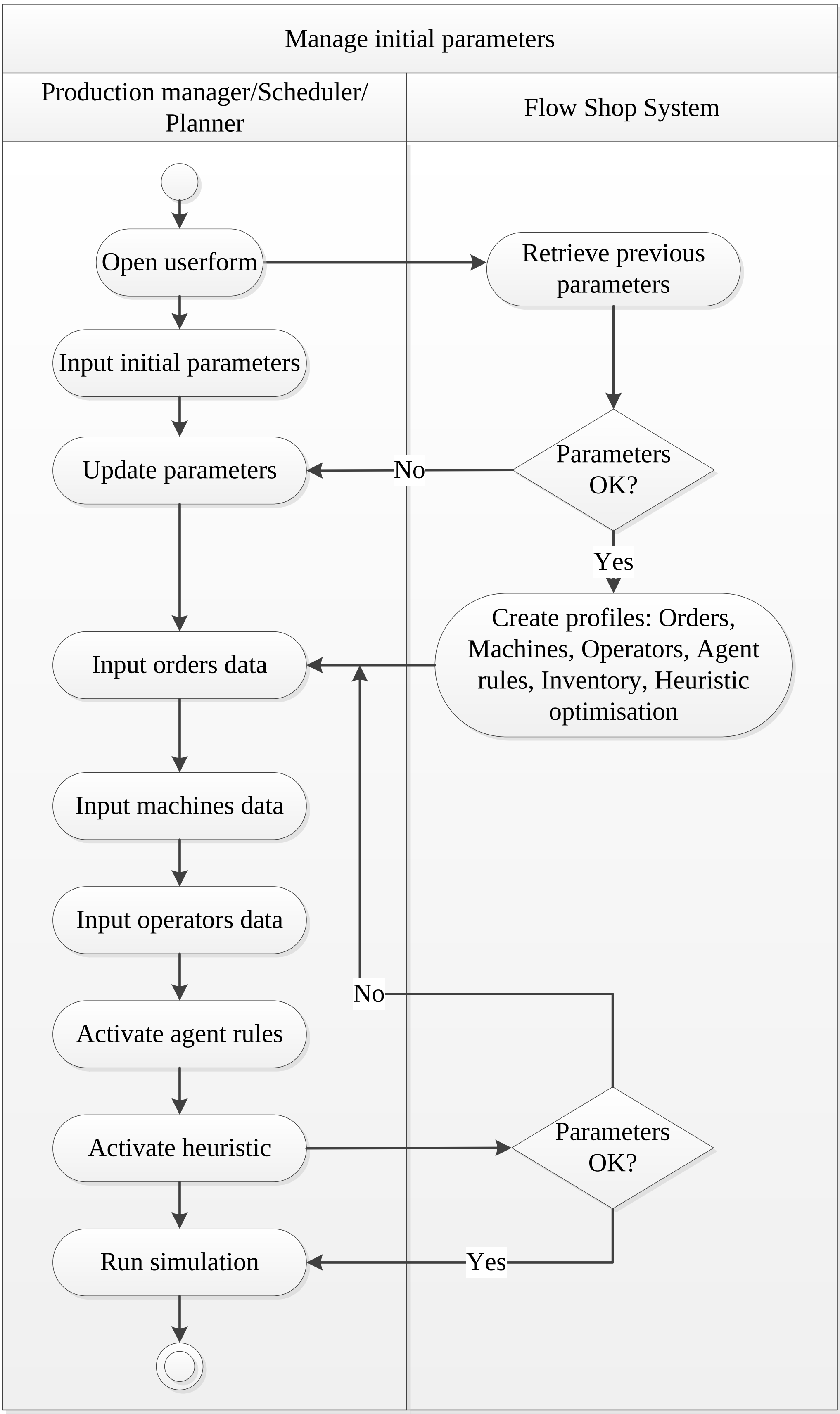


Figure 4-5: Initial parameters activity.

The managing initial parameters activity is performed from two sides, the user (Production manager, scheduler or Planner) and system (Flow Shop) sides. It commences from the user side userform is opened for initial parameters input. In case there has been previous parameter input, the flow shop system retrieves stored data. In both ways, the parameters are checked to match with intended current requirements and updated by the user if there is any discrepancy. The user input further details of agents (orders, machines and operators), selected to activate heuristic algorithm to take effect when required. And finally, the user runs the simulation, the action which terminates the initial parameters activity. From the scheduling point of view, Figure 4.6 depicts the activity diagram below.

Figure 4-6: Schedule activity diagram.

There are three sides to scheduling activity, the flow-shop system, heuristic algorithm and the agent-based model. The scheduling process commences in the flow shop system where the disruption is also checked for a rescheduling if there is any disruption. In case of disruption, the activated heuristic algorithm to tackle disruption problem can be implemented as required. The various activities involved in the application of heuristic algorithm are the executing of inventory borrow, utilisation of available time and the execution of order inventory level replenishment. Meanwhile, the actual production process of the scheduled order is performed within the agent-based model side. In this ABM side, the agents (order, machine, and operator) and resources are allocated and managed through agent manager for the smooth running of the process. Most significantly within the ABM, the available time for inventory replenishment is provided if there is any for the heuristic algorithm side. However, agent-based calculation of available time even when there is no disruptions helps to continually sustain inventory to the desired levels. The process results is saved through the ABM and send for storage in the flow shop system. The activity diagram for managing the simulation activities is presented in Figure 4.7 below.

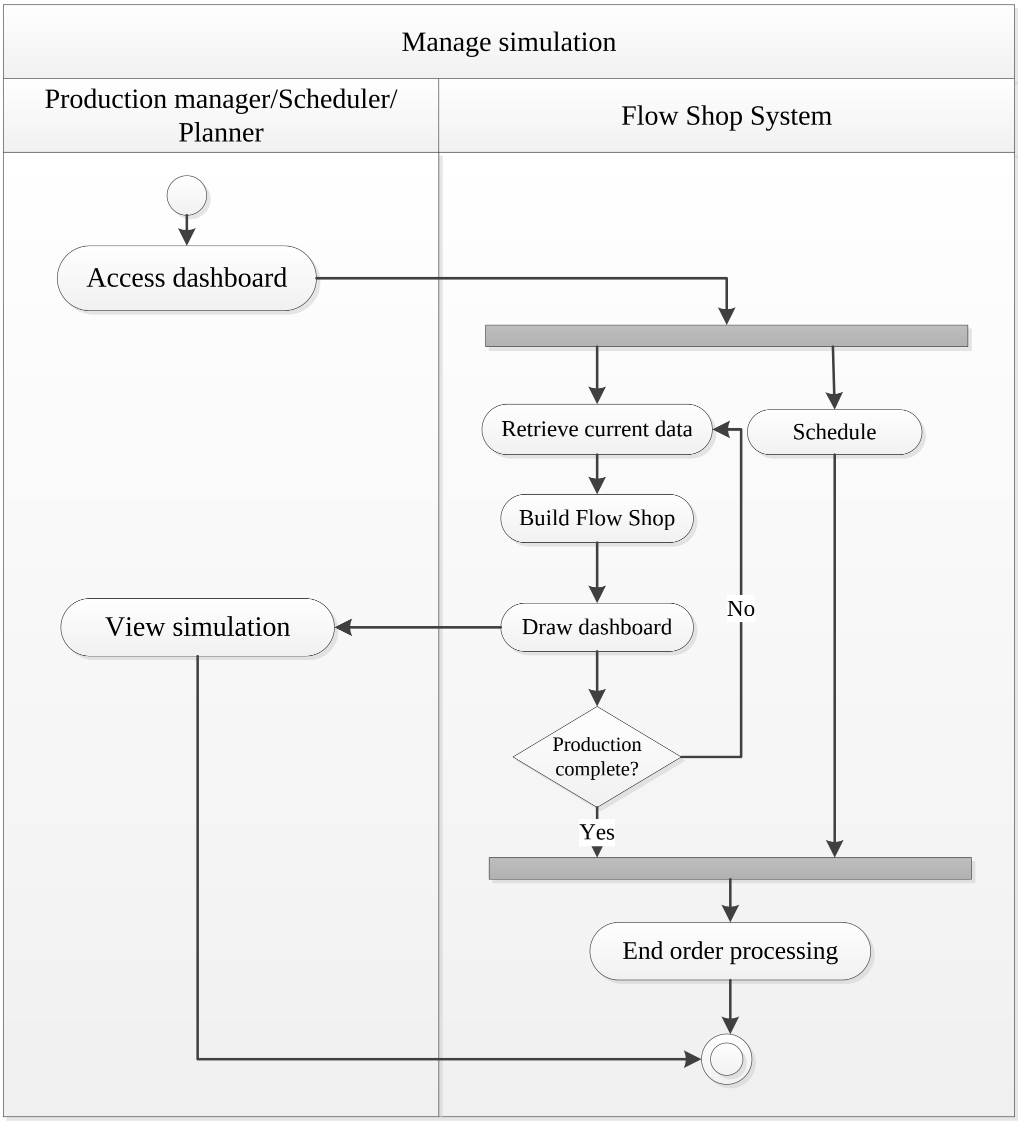


Figure 4-7: Simulation activity.

In the activity diagram for managing simulation, there are two sides; the flow shop system and the user side. The user through the user interface gain access to the dashboard to perform operation such as retrieving current data and activating scheduling process. Within the system, the flow shop is built, dashboard is drawn for order processing, while the simulation can be viewed from the user end through dashboard process animation. The activity diagram for managing the results is shown in Figure 4.8, which also has two sides such as the user and the flow shop system sides. The user can access results and trigger the system to build reports, generate result graphs, which can be viewed and analysed by the user.

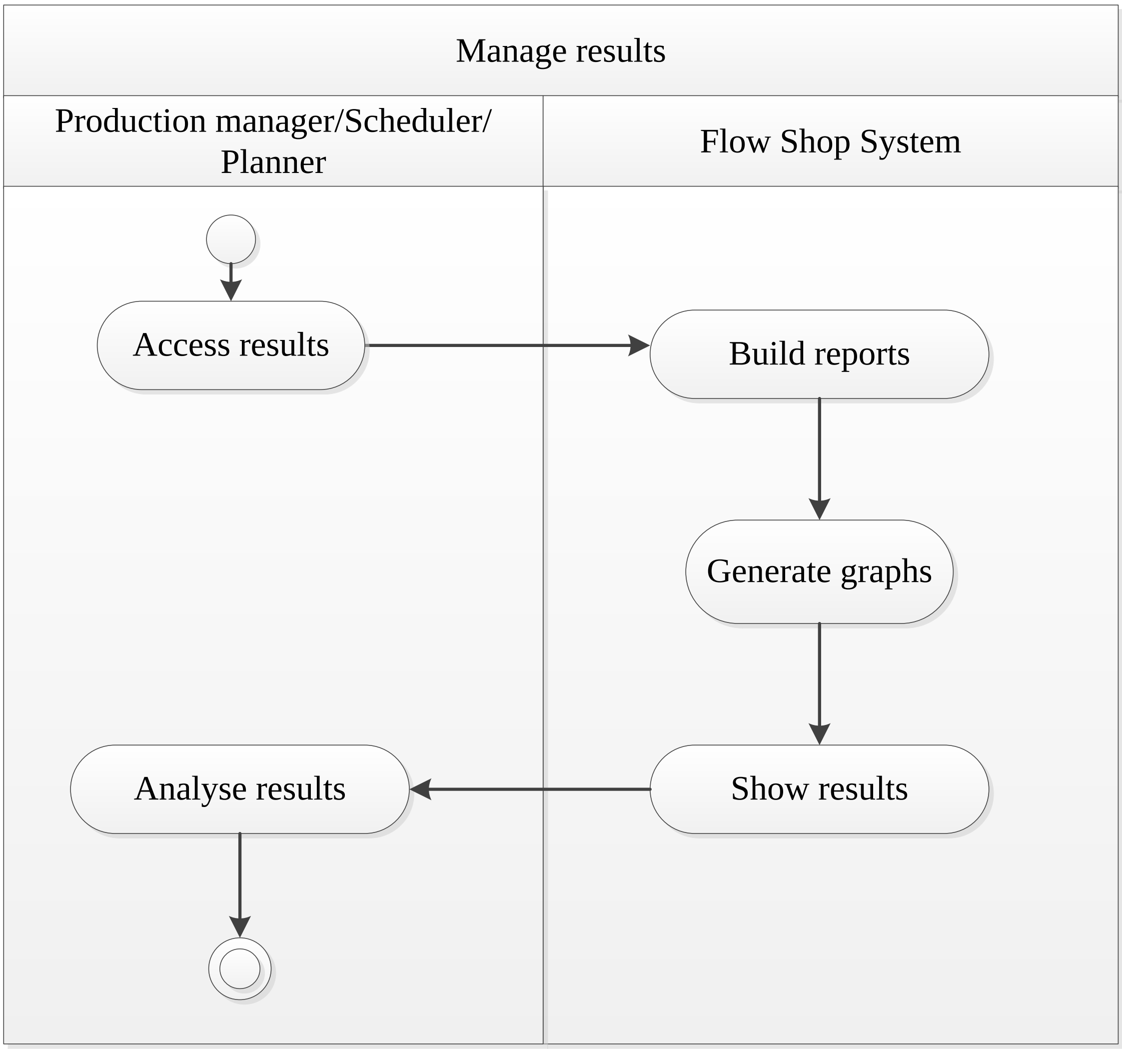


Figure 4-8: Managing results activity diagram.

4.5: The data flow diagrams

In object-oriented modelling, data flow diagram is used to represent the flows of data from one process to another within the given system environment. In this study, the data flow diagram is adopted to provide a simple, intuitive means of describing the developed system processes without unnecessarily detailing the core back-end program processes. It is considered attractive method because it presents the system data flow from user perspective rather than from the system perspective. In this chapter, three data flow diagrams are presented, they include the data flow diagram for Agent-Based Simulation and Heuristic

Algorithm System (Figure 4.9), the data flow diagram for Agent-Based Simulation (Figure 4.10); and the data flow diagram for Heuristic Algorithm (Figure

4.5.1 Data flow diagram for agent-based simulation and heuristic algorithm system.

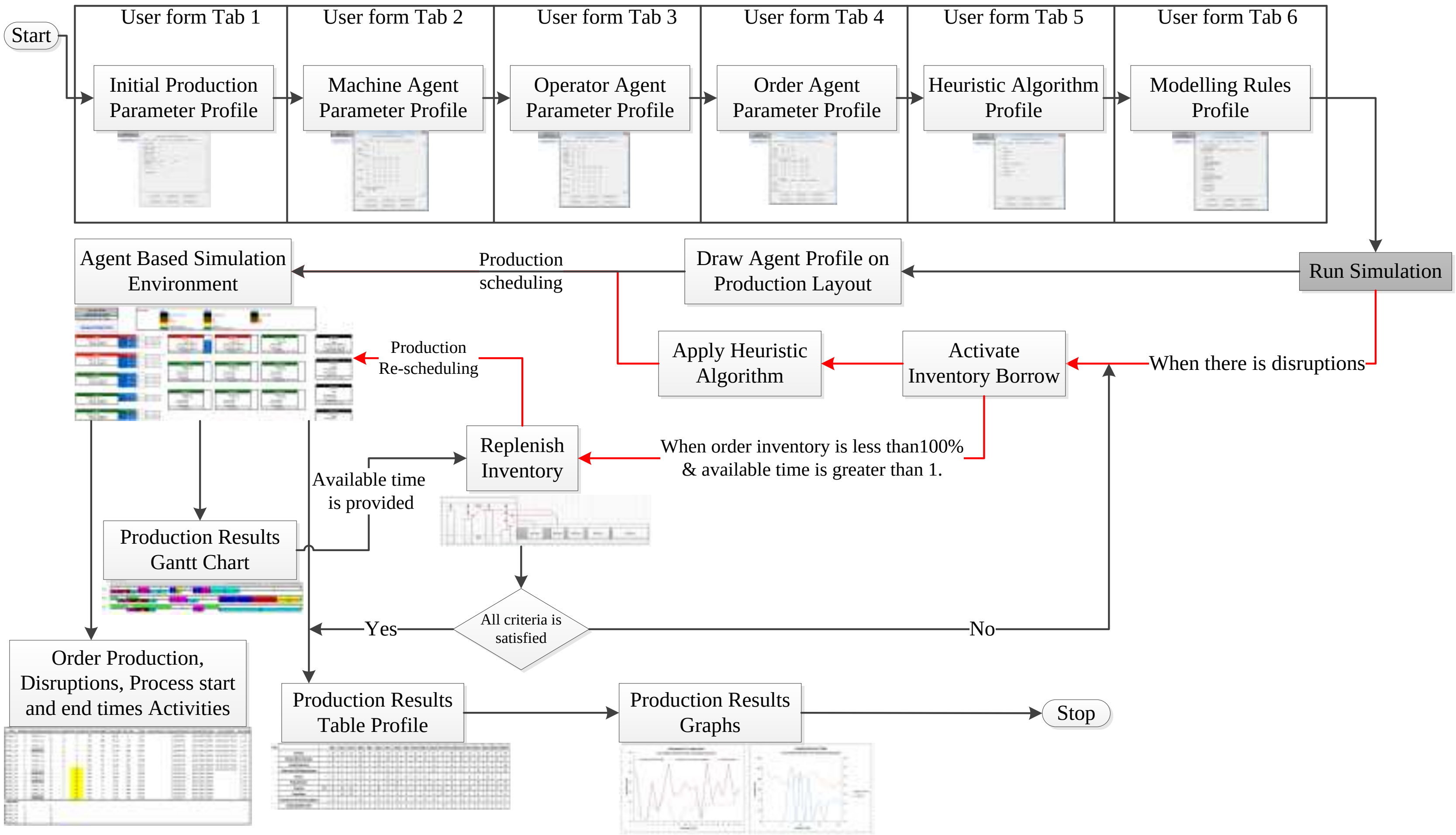


Figure 4-9: Data flow diagram for Agent-Based Simulation and Heuristic Algorithm System.

The flow of data within the integrated agent-based and heuristic algorithm system is shown in Figure 4.9. At the start through the user form tabs, there are initial parameters and agents' profiles where input data flows into the system operation through the simulation run button. The initial data is considered for both disruption and for no disruption conditions. The data details possess action to draw production layout, apply heuristic, activate inventory borrow, and replenish the inventory after borrowing. The data is carried on to the actual agent-based simulation where they serve as input for the process. After the simulation process, the data is transcribed into measurable information in form of results. The results, such as the Gantt chart, tables and graphs are presented to the user through the user interface.

4.5.2 Data flow diagram for agent-based simulation.

As the traditional simulation method, data flow within the simulation commences through the user form input through to data processing and the result output. There are six forms for initial data input to start the simulation process (as shown in Figure 4.10 below).

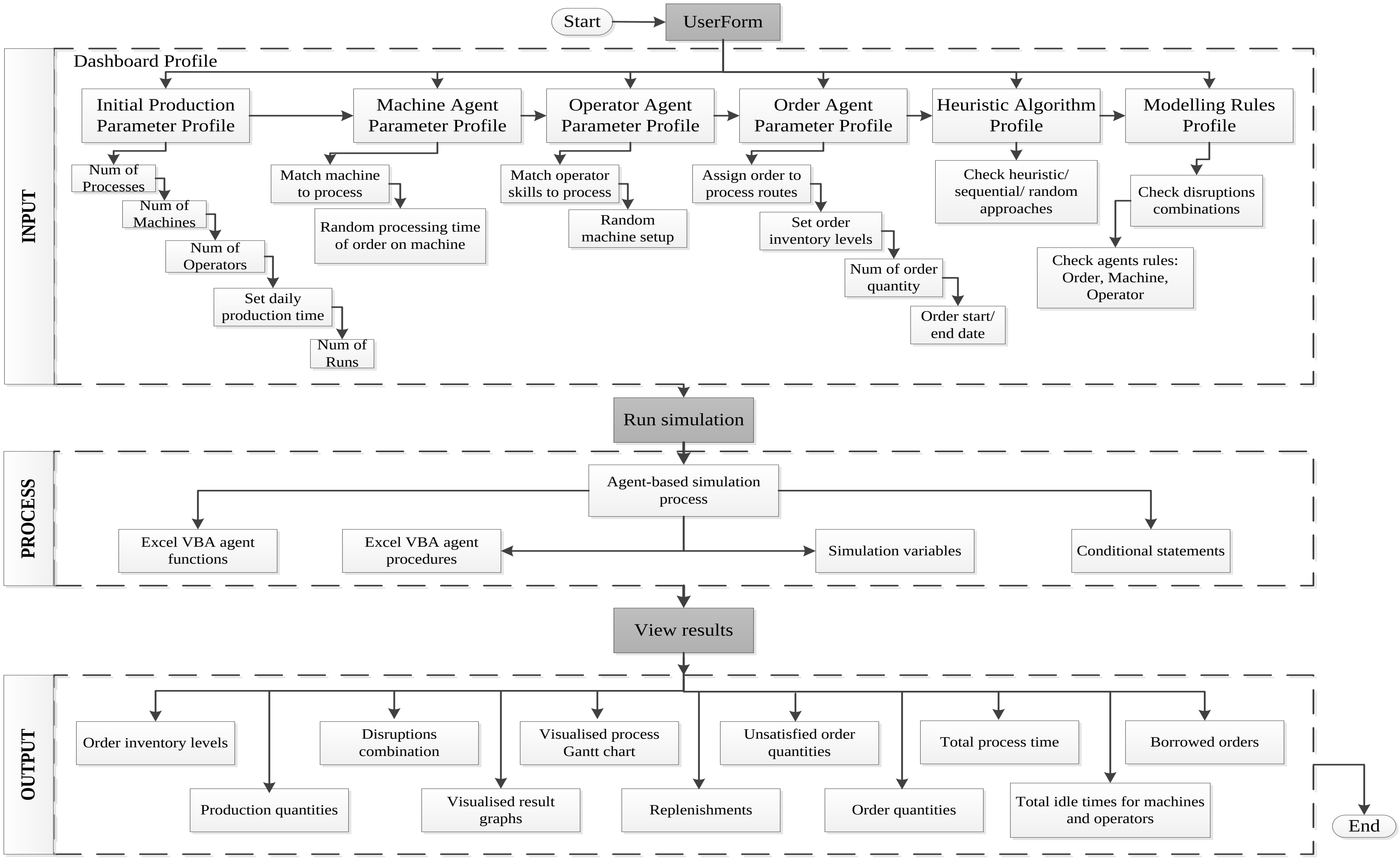


Figure 4-10: Data flow diagram for Agent-Based Simulation

They are the initial production and agents' parameter profiles as well as the modelling rule profile. From the initial production parameters, the number of processes, number of machines, number of operators, and number of orders are set. Also, in this profile, the number of simulation runs and production period is informed. From the machine agent profile, machines are matched with processes they can perform, and the random generation of machine process time is activated. From the operator agent profile, operators are assigned to jobs through machine matching based on skills. And the random generation of operation setup time on machine is activated. From both heuristic and modelling rules profile, system action based on circumstances is activated.

In this section, random generation of process time and setup time is mentioned as a generic approach when no real data is available. However, in the experimentations (discussed in section 6), data from the real-life case study problem was used.

The simulation based on Excel VBA and all related programming functions, variables, procedure and conditional statements as indicated in Figure 4.10 are effective to the agent-based simulation process. From the agent-based simulation programming point of view, the condition statements refer to "if-then statement". They are pre-determined programs to help in decision making process of agent-based simulation. The outcome of the simulation present results in different categories are shown. The output of the simulation process includes order, inventory and replenishment information as well as the graphical representations of the results.

4.5.3 Data flow diagram for heuristic algorithm.

The heuristic algorithm specific data flow diagram is presented in Figure 4.11 below to show the flow of data from the start to end of heuristic algorithm activation within the system.

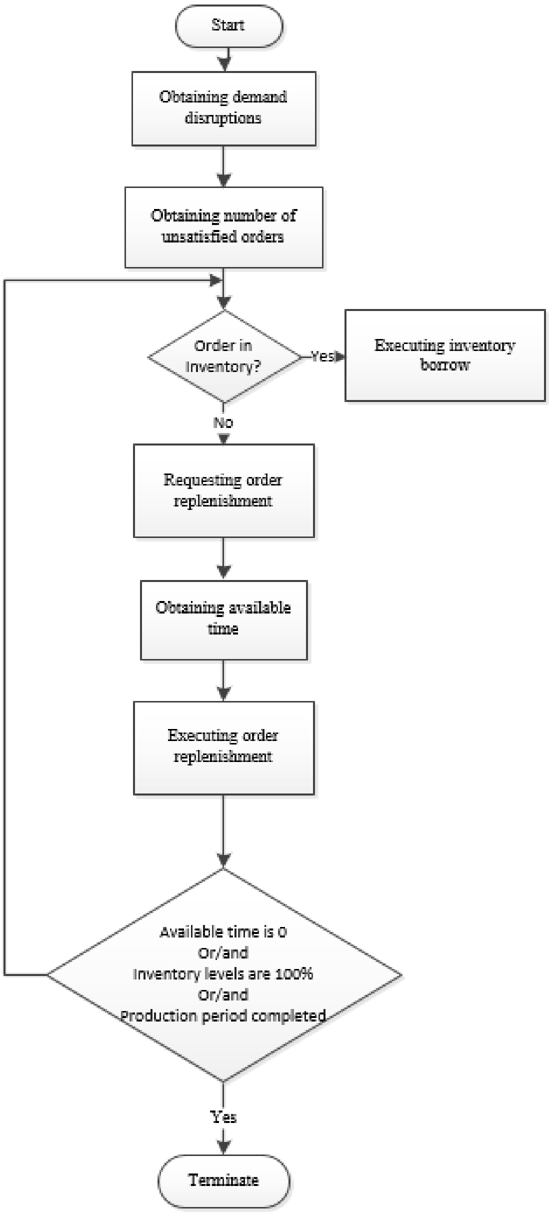


Figure 4-11: Data flow diagram for Heuristic Algorithm

The heuristic starts by obtaining demand disruption, and the number of unsatisfied orders as a result. The inventory borrow is executed based on the obtained data. As order has been borrowed from inventory, replenishment execution is done by obtaining available time from ABM based on inventory request. This data flow process continues until all condition highlighted are satisfied and then the process terminates.

4.6 Userform dashboard

The main userform automatically pops out when the developed flow shop production system is launched. Some of the details of the userform dashboard is discussed. Figure 4.12 shows the system data form button that can also launch the main userform.

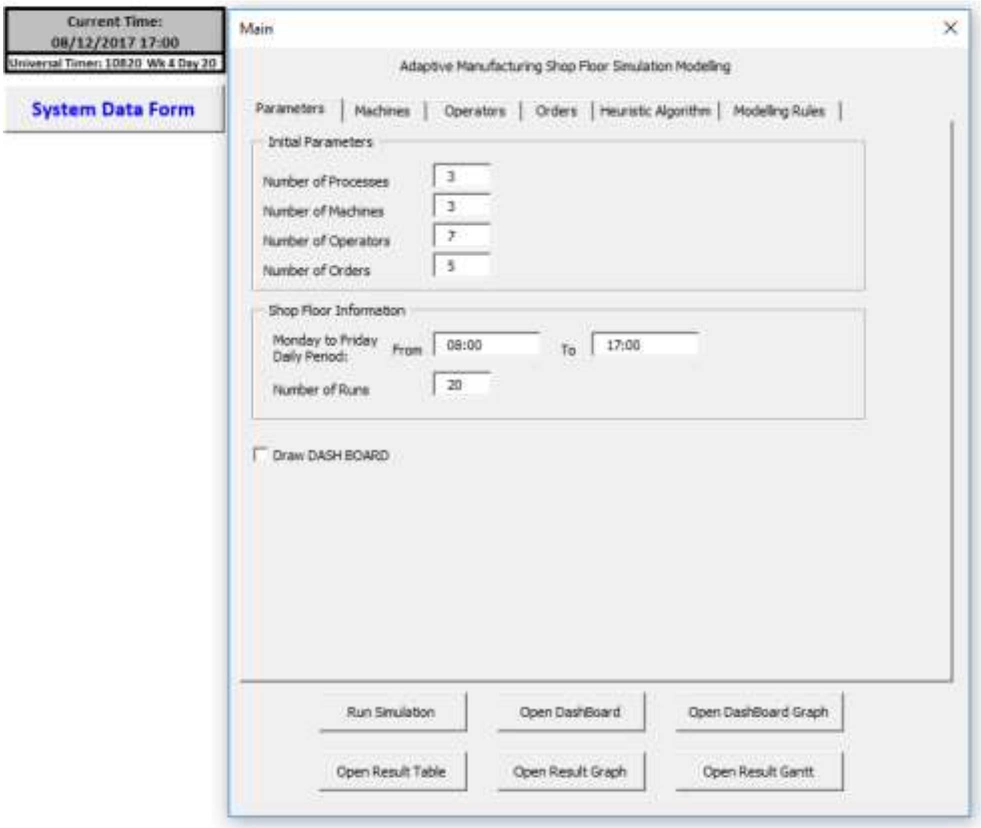


Figure 4-12: The initial parameter userform.

4.6.1 The System Data Form

It is the button that opens the 'Main' user form where user can input simulation data relating to machine data, order data, operator data, modelling rules as well as the heuristic algorithm, but included system navigation butto

4.6.2 The Navigation Buttons

The navigation buttons highlighted below underneath the main userform are placed to move around the system based on specific sheet tab of interest, e.g. to view dashboard, dashboard graph, result table, result Gantt and result graph as well as running the simulation.

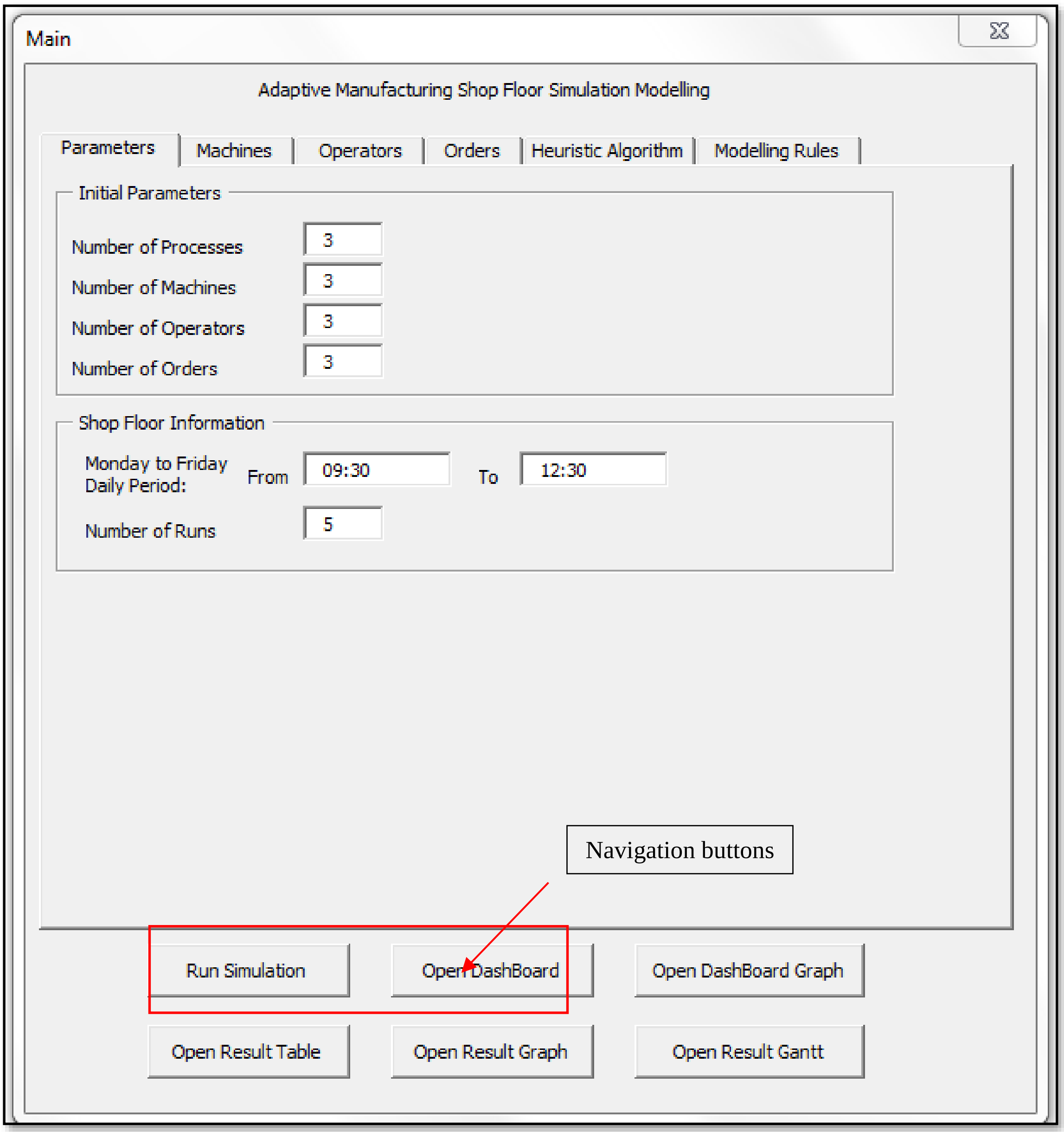


Figure 4-13: Figure Main user form initial input parameters tab

Apart from the run simulation button which must be clicked to run the system, other buttons are present as alternative buttons that can be used to navigate around the system for specific view.

4.6.3 The Main User Form

The main user form is a multipage userform consist of six tabs (each for parameters, machine, order, operator, heuristic algorithm and modelling rules) and includes navigation buttons underneath. Each tab enables the user to define input information about the system entities (agents). From the main user form is the order values, number of machines and operators are given.

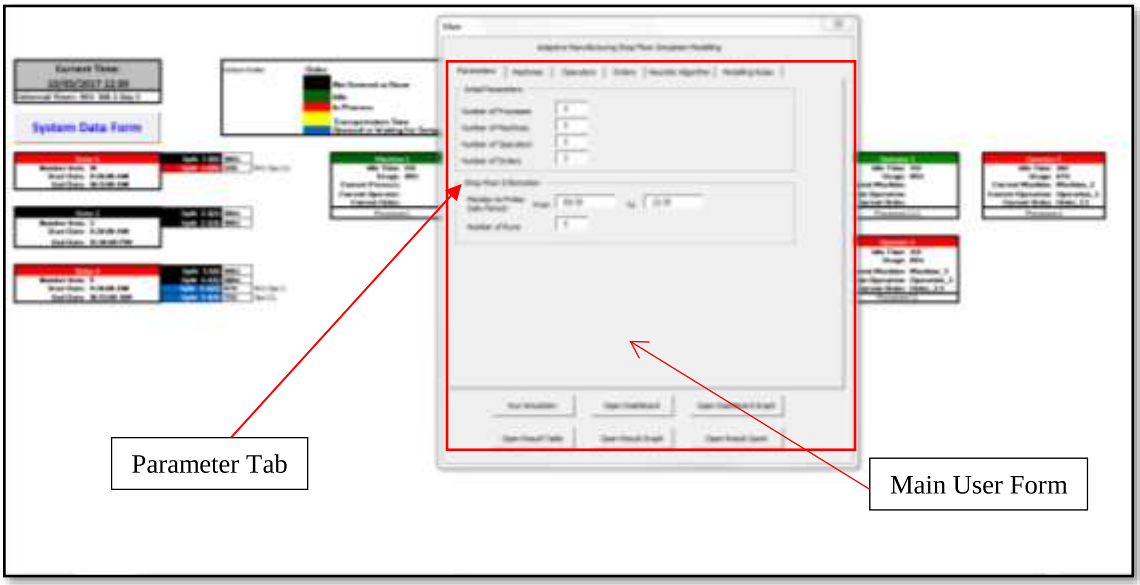


Figure 4-14: Dashboard main user form

4.6.4 Parameter Tab

The first page of the main multipage user form is by default the parameter tab. It consists of two sections:

- The initial parameter and
- The shop floor information

The initial parameter is where number of processes, number of machines, number of operators and number of orders are defined. In the scenario example, the number of processes is equivalent to the number of machine because the problem case is that of a flow process with sequential operation. This means one machine is assigned to one process of which the second process is dependent on the first and so on. However, the system design is generic and can accommodate production process with shared machine and operator resources as well as parallel processes with alternative options. In the case of alternate machine, more than one machine can be assigned for one process.

The flow shop information is used to specify daily production period (start and end time of operation) and number of runs. The number of runs means production days that is, one day for one simulation run.

4.6.5 Simulation Environment

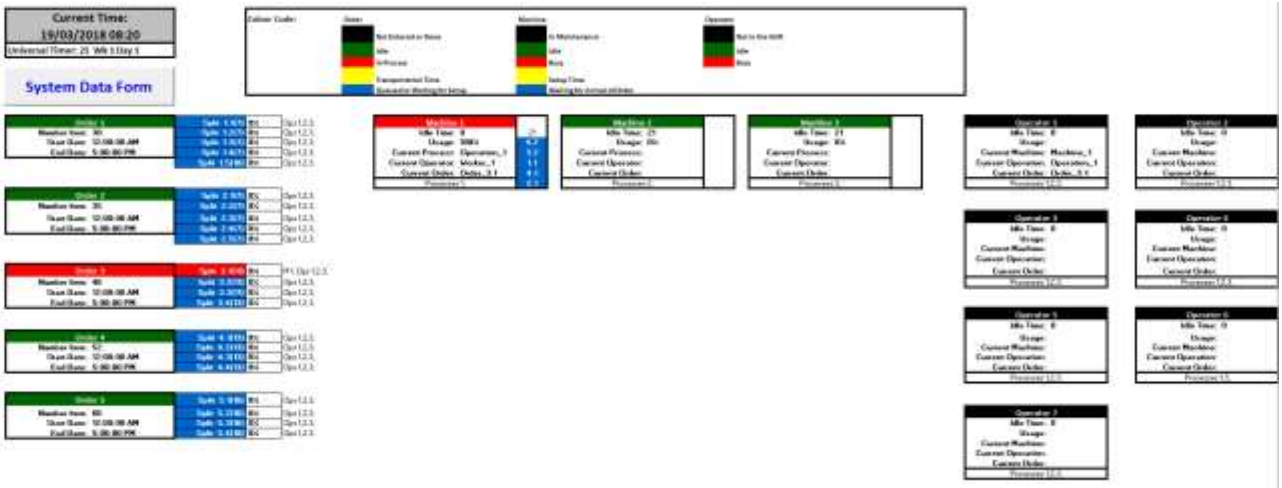


Figure 4-15: The simulation system environment.

The simulation environment is embedded in the dashboard sheet tab. The environment is where modelling, that is, order processing activities is done have three agents' section on the spreadsheet such as the order, machine and operator areas. Each assigned space is drawn corresponding to the number of order, machine or operator that is been defined from the input parameter. The simulation system agent area shows the area occupied by individual agent as defined at the start of each simulation run. The areas are drawn downward to accommodate the number of orders, machines or operators involve in the simulation processes.

4.7 Production, production times, and key performance indicators (KPIs) analysis flow diagrams.

It is important to give further details and understanding of the flow of data and information through the system specifically for the purpose of analysis. In this section, flow diagrams for production, production times and Key Performance Indicators (KPIs) analysis are presented (Figure 4.17; Figure 4.18; Figure 4.19). As other diagrams presented in previous sections, the analysis diagrams are form a simple and fundamental step that are being followed through the analysis process. It is, however, a pictorial glimpse to key system aspects involved in analysing the production, production times and the KPIs. The KPIs are:

- Number of late/unsatisfied orders
- Machine utilisation and Operation utilisation.

4.7.1 Production analysis diagram

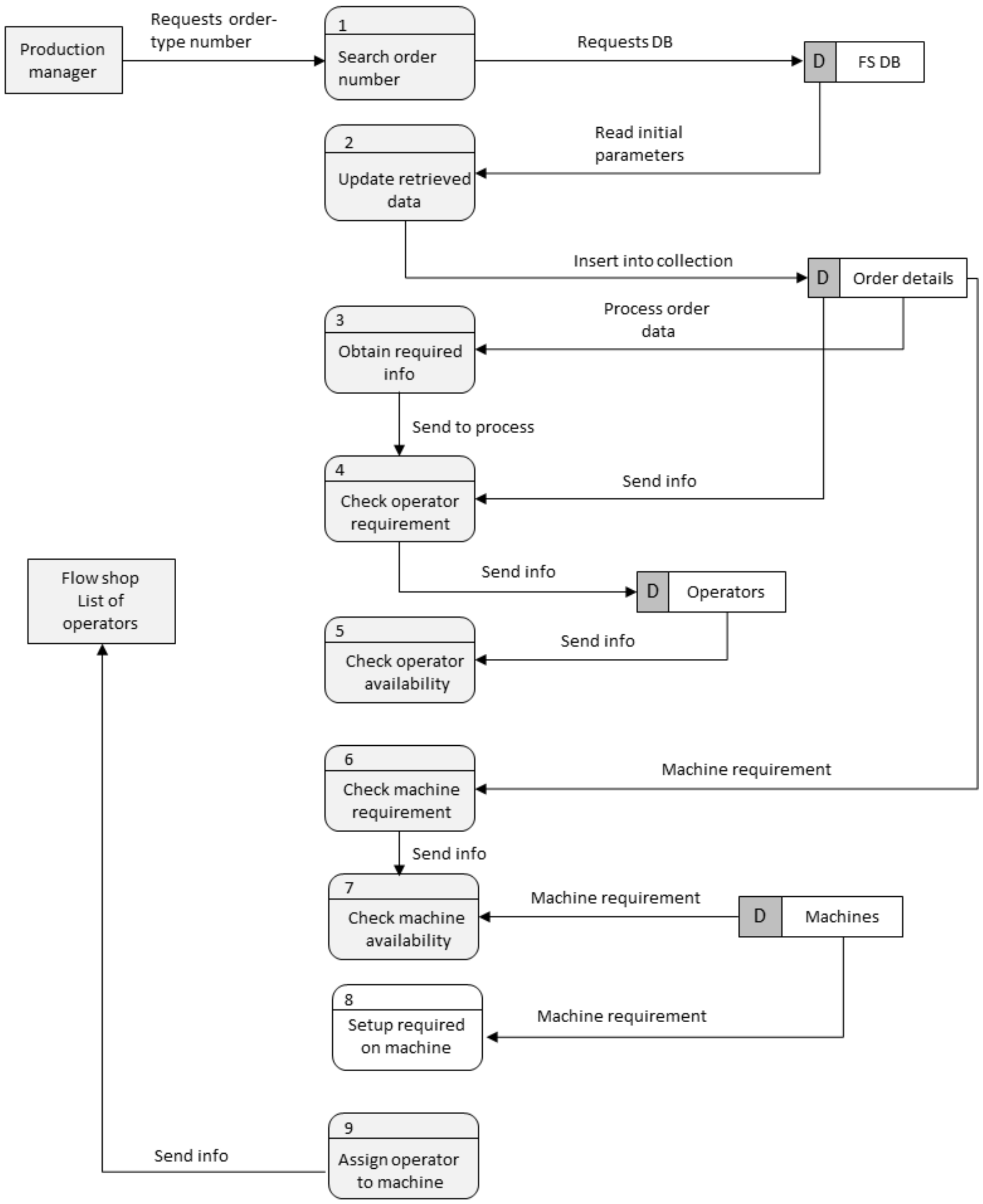


Figure 4-16: Production analysis flow diagram.

In Figure 4.17, the production analysis flow shows the interaction of production manager with the flow shop database (FS DB) in order processes. It includes the assigning machine requirements, operator allocation and their availability in the process. Production manager requests order type number, which has been initially saved in the flow shop system database. The order number is searched in process 1, after which the initial production and order details are read from the database.

In process 2, the retrieved data is updated for correctness of the intended operation. And so, the updated order details are inserted into the collection. For order to be processed, additional order information is required, among which are operator and machine availabilities. Therefore, in process 3, operator requirement information about availability is sent. Also, from order details, machine requirement information is requested to obtain machine availability, and setup requirement such as setup time and number of setups. Finally, in process 9, based on the list of available shop flow operators, operators are assigned to machine for order processing to start.

4.7.2 Production time analysis diagram

The production time analysis in (Figure 4.18) is significant in this report because of the nature of the research problem and proposed solution approach. In order to solve the production disruptions problem that occur within the flow shop, the study take advantage of time relationship in the event of disruption. In the borrow of shortage orders and replenishment of inventory, total process times, and setup times are calculated based on order start and end time to derive the available time which is used for replenishment purpose.

The job manager searches for order number and type through the flow shop database system. The details id sent to view in order to obtain the start and end date of orders from the retrieved order data. From the retrieved details, the total process time for each order is calculated as well as the setup times during the defined production days and the entire period. When disruption occurs, by matching the disruption total process times with the originally expected process time, and setup times, the available time is obtained. The system creates a visual representation of the process, setup and available times in form of Gantt chart. The Gantt chart is stored and can be view for production time analysis purpose. In a situation where there is no disruption, and the available time is calculated, the inventory would be sustained using the available time while new production schedule is been generated.

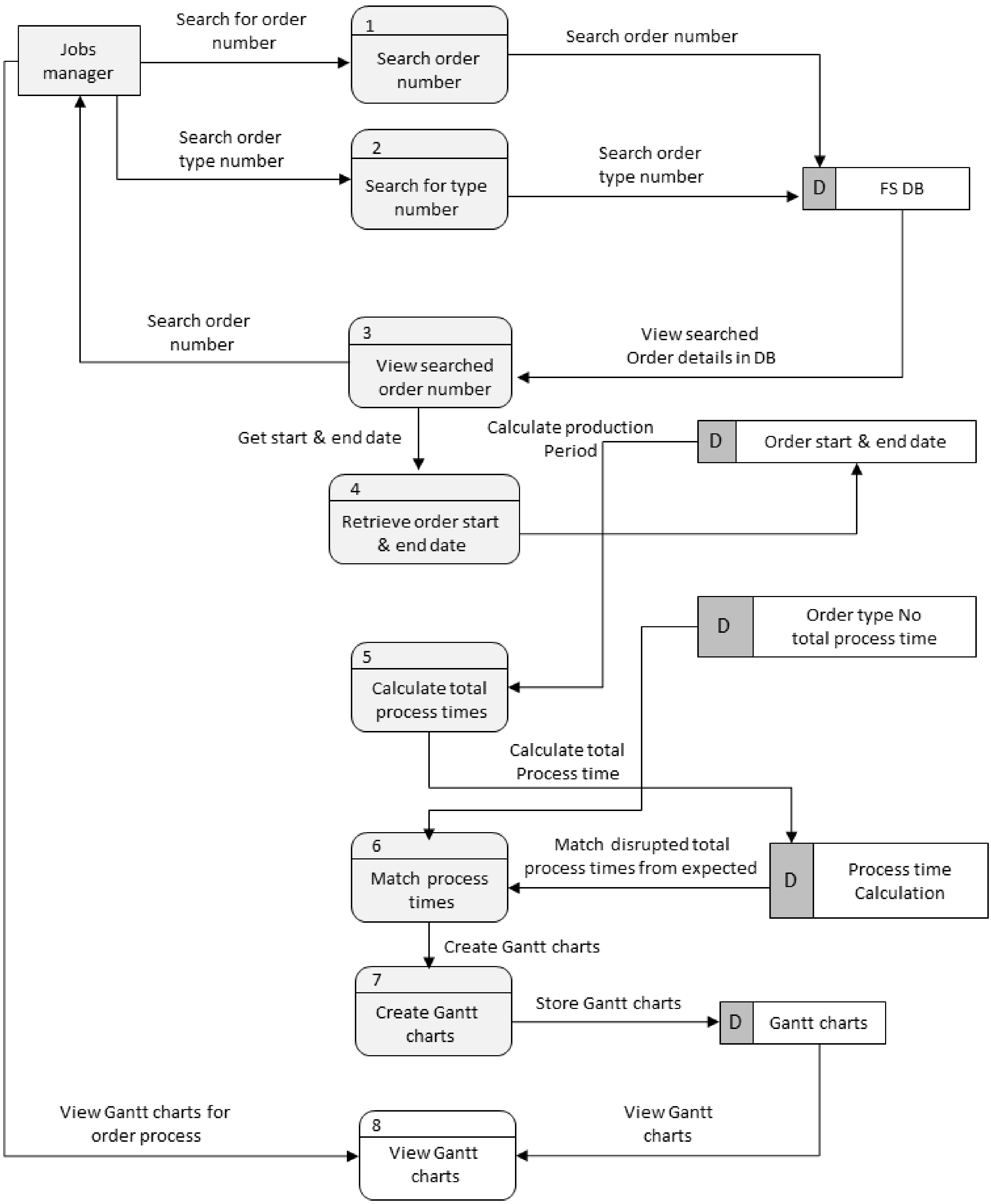


Figure 4-17: Production time analysis flow diagram.

4.7.3 Production KPIs analysis diagram

In the KPIs analysis diagram (Figure 4.19), the creation of the predefined flow shop production KPIs through the order process results stored in the flow shop database is represented.

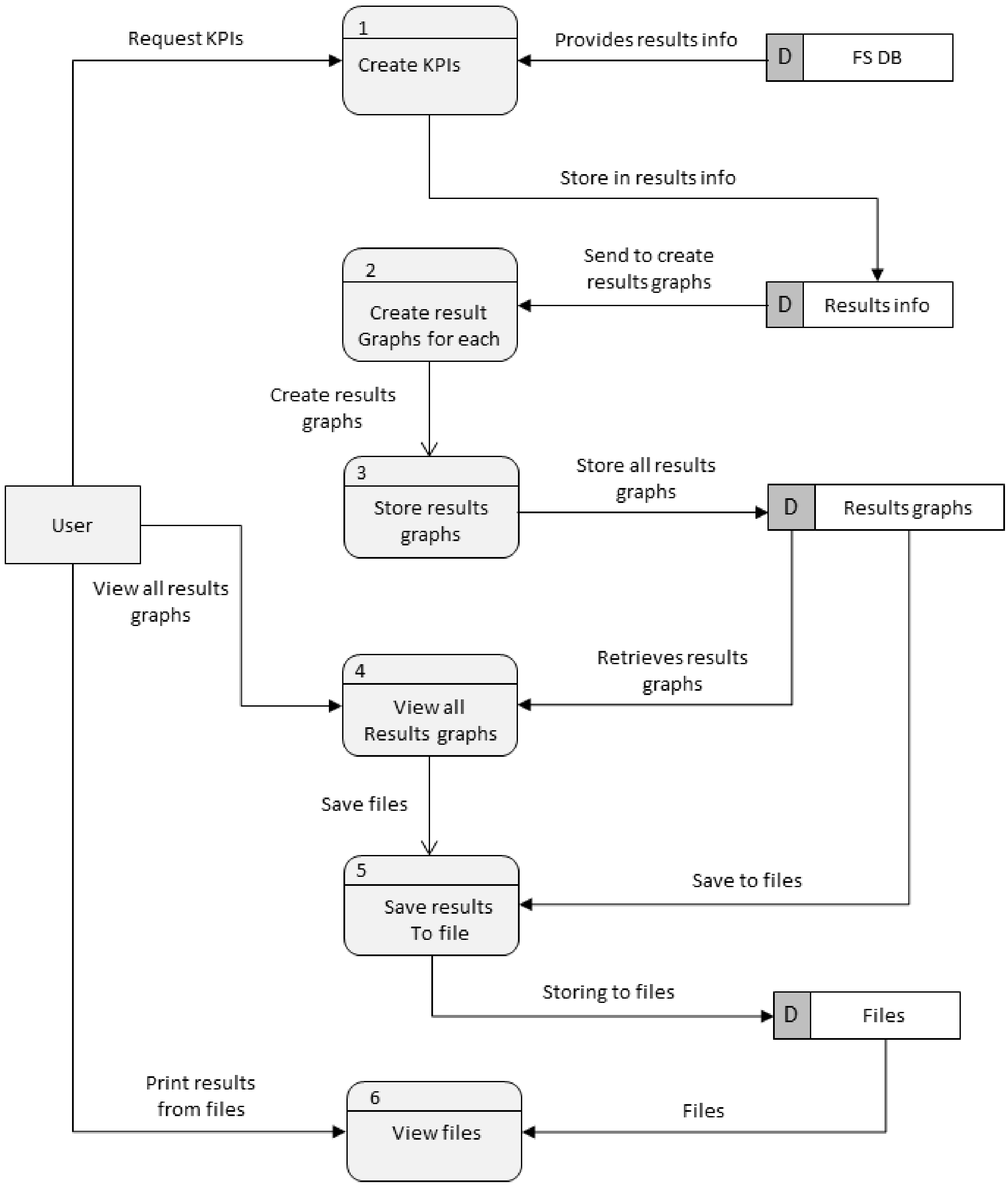


Figure 4-18: Production KPIs analysis diagram.

The system user (production manager, scheduler or planner) can request PKIs for analysis purpose. When the KPIs is requested, it is been created through the flow shop database where the production results information is saved and provided. In process 2 based on the production KPIs, related process results graphs are created for each KPIs. The created results graphs are then stored in the result graphs location within the flow shop system database (FS DB), where they can be retrieved to view and re-view by user. The results essentially are saved to files where they can be used for printing references and further analysis.

Chapter 5: The Case Study

5.1 Introduction

The case study chapter presents the report about Unipart Eberspacher Exhaust Systems (UEES) and its production processes. This selected case study is crucial to the current research as an OEM company with related disruption problems, and where the developed system can be experimented. At large, the manufacturing industry such as UEES is one of the most important sectors in national economy growth. Its production behaviour is paramount and of great concern to stakeholders.

In this chapter, brief information about the company is given and the manufacturing operation is presented. The operation processes a specific product family is highlighted, which is product with two production line of three product numbers each is chosen to understand its in-depth process. Diagrams that represent different aspects of the industry, the production floor layout, operation procedures, process map IDEF0 depicting the processes overview and delays involved, are presented. These diagrams are presented to help visualise and hence, understand various activities involved at different levels as well as products.

5.2 UEES Company Profile

Unipart Eberspacher Exhaust Systems (UEES) is an Original Equipment Manufacturer (OEM) of automotive parts. The company is part of the Unipart Group which have other divisions including Unipart Logistics, Unipart Rail, Unipart Expert Practices, UTL as well as Unipart Manufacturing which UEES belongs alongside Kautex Unipart Ltd. UEES is a first-tier supplier for the automotive industry with accredited quality to support customer base for British, European and Japanese vehicle manufacturers. This vehicle parts and components manufacturing company is based in Coventry, United Kingdom. It currently has major vehicle manufacturers in the world, among which are Jaguar Land Rover (JLR) also based in Coventry, BMW, Aston Martin, and Ford Motors as customers. The company is specifically known for five main types of product families of different volumes and varieties, which are produced onsite and despatched to these customers accordingly.

These products as shown in Figures 4.14 includes exhaust systems, steel fuel tanks, fuel filler neck, diesel particulate filters, fabricated manifolds, engine components, and catalytic convertors, designed and manufactured by the company. Raw materials are sourced from wider range of suppliers both locally in the UK, and internationally in the EU (Germany, Czech, and Italy), and in Japan, China, India, and South Africa. These raw materials include straight pipes, presswork, ceramic bricks, and metal sheets.

5.3 Manufacturing Facility

As new market emerges, competition increases, and the production processes become more complex. The introduction of new multiple products requires the development team to take-up significant number of robots and machine time in order to create requirements for new products. Multiple products mean significantly high-volume increase, which the production planning struggle to accommodate.

In a situation where machine breakdowns, material shortage, scrap production, resource availability and high-quality standard are factors to consider in production process, meeting customers' demand becomes challenging.

The manufacturing facility of the company is presented in an interactive figure as below. It shows an interaction and activities that exist in dealing with customers’ demand. It comprised of both internal and external units. The suppliers and customers are considered here as external units of manufacturing facility while other aspect of productions like production control, warehousing, inventory control, shipping, purchase and the actual manufacturing stages are considered as internal units.

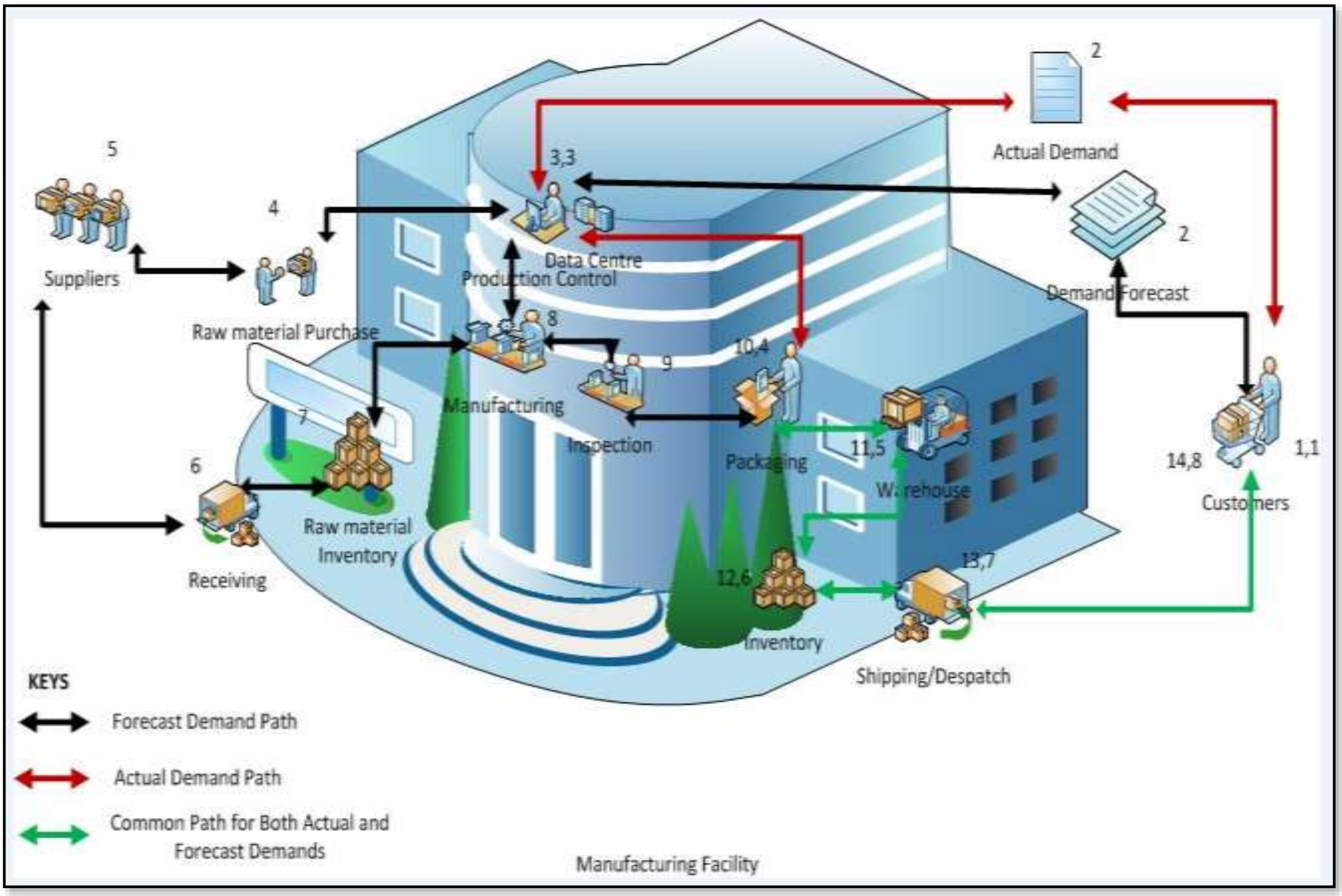


Figure 5-1: Manufacturing Facility

Manufacturing facility activities is initially triggered by customer demands. In this case, there are two stages of demand received from customers. The first is the demand forecast, used to project or inform the suppose quantity and specification of products needed. This is acted upon by the production control unit by requesting (purchase) raw materials from external suppliers. Stock the material for production and send information to the flow shop to start production. The second stage of customer demand, which is known as the actual demand is considered and finally compared with the actual production to meet customers demand. As shown in the Figure 5.1, there are three (3) paths indicating demands. The demand forecast is represented by the black path, red by the actual demand and the green path represent a common path. This common path is where comparison takes place, where the despatched finished products are, what is required.

Likewise, there are numbers associated with the paths. Initial demand forecast follows path numbers 1-2-3-4-5-6-7-8-9-10 and stop at a point where actual demand is met. Actual demand, which follows path numbers 1-2-3-4, became a common with the initial demand from path numbers (11, 5) - (12, 6) - (13, 7) - (14, 8). This meeting point is where sorting of products in sequence in done based on actual demand requirement.

5.4 Flow Shop

The flow shop is organised in such a way that enables incoming raw materials stocking in an area where they are been picked up in pallets with the use of pump truck into production area consisting of different operation cells. Each cell in the production area is layout based on different product families. In Figure 5.2, which depicts a layout for a single product number (indicated as product type A); the product passes through all the processes in the layout. From raw material area to cup forming, then transported for bending, after which robot welds other parts to it. The product is air test for check leakage, any identified leakages are then sent for repair before assembly process. Final quality checks are done to ensure products meet required customers' specification.

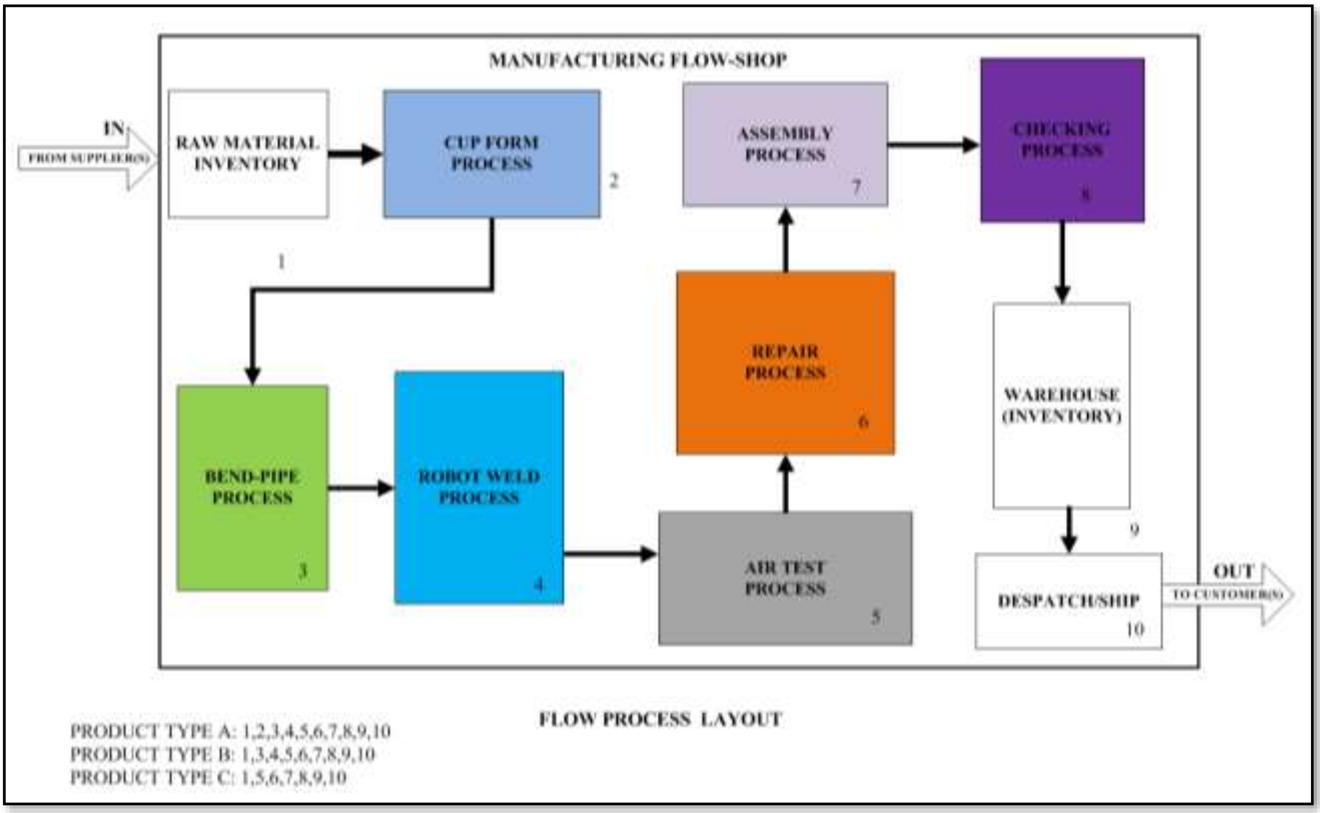


Figure 5-2: Flow Process Layout

The product type with corresponding product number follows production route related to its specification. After the raw materials meant for its production is shipped in from suppliers, the materials are temporarily stock in an open storage (raw-material inventory area). This is where they will be picked up once customer demand calls has been sent to the production floor. For the product type under review, the process layout shown in Figure 2 represents the process routes it follows.

The company receive customers demand in two formats: one is through Daily Call-In (DCI), which is visible through electronic data interface (EDI). This type of customer demand is received daily and its spread over two weeks in forecast of quantity required. Considering customers' safe stock level, it is important to fully (100%) satisfy this requirement. When this is not possible, the remainder is added to the second type of demand format called planning data- release summary. This shows the rollover quantity based on the daily call-In. It is received on a weekly basis. It shows the required and released quantity accumulated over a period, normally two weeks. In Figure 5.3, the actual real-life flow process layout is presented.

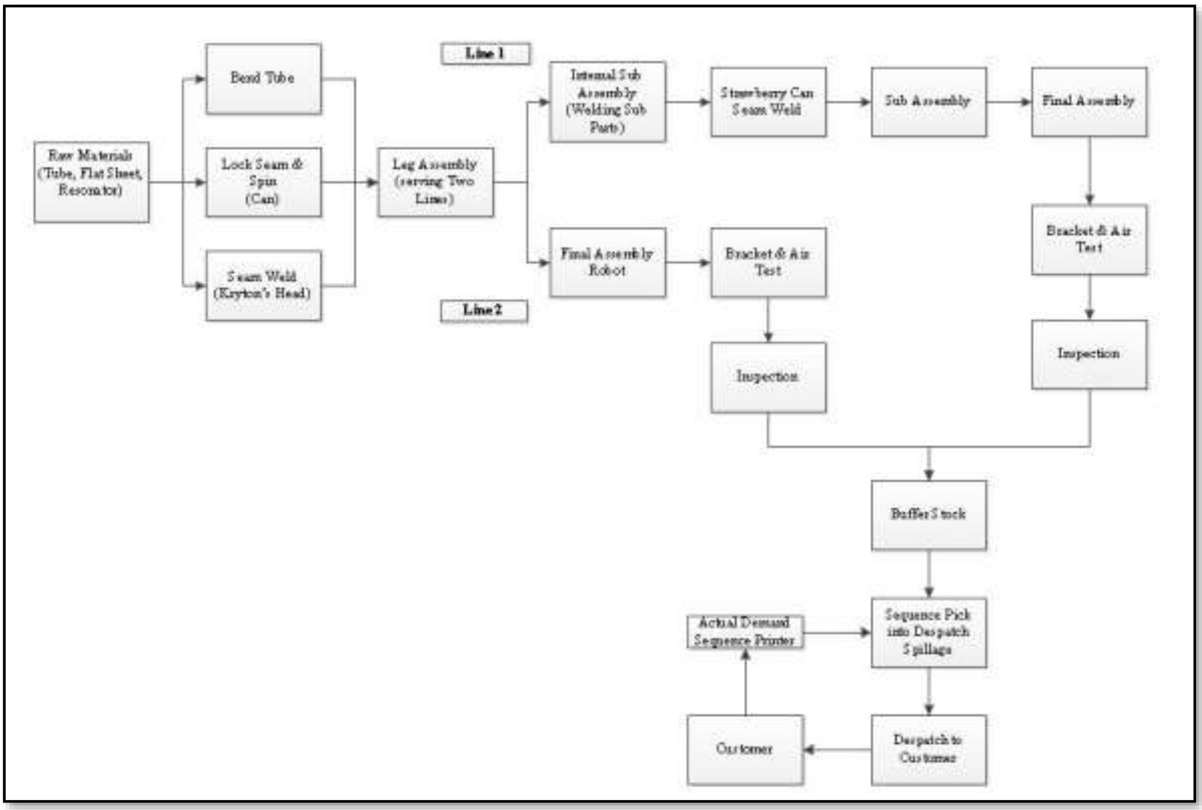


Figure 5-3: The UEES Flow-Shop Process Layout

There are two production lines represented in the process layout above. This layout is related to all the company products, including the fuel filler neck, the production path of which has been followed through in this study. All raw materials for all products types proceed by following different paths that is specific to their production requirements. There are three possibilities for the materials, some go into tube bending machine area, some into lock and spin to make can while others go into seam weld also called Kayton's Head. The three different paths meet again at the leg assembly machining area which serves two production lines onwards. Two production lines of different product types undergo sequential welding, sub-assembly, testing and inspection processes as indicated in the layout. After the inspection production of finished products is the buffer stock (known as inventory storage). This is where customer orders are selected according to requirement in terms of quantity, delivery time and sequence and dispatched to customers

5.5 IDEF0 for UEES Product Processes

A business process mapping for the company's product specific processes have been developed using IDEF0 as shown in Figure 5.4a and b below.

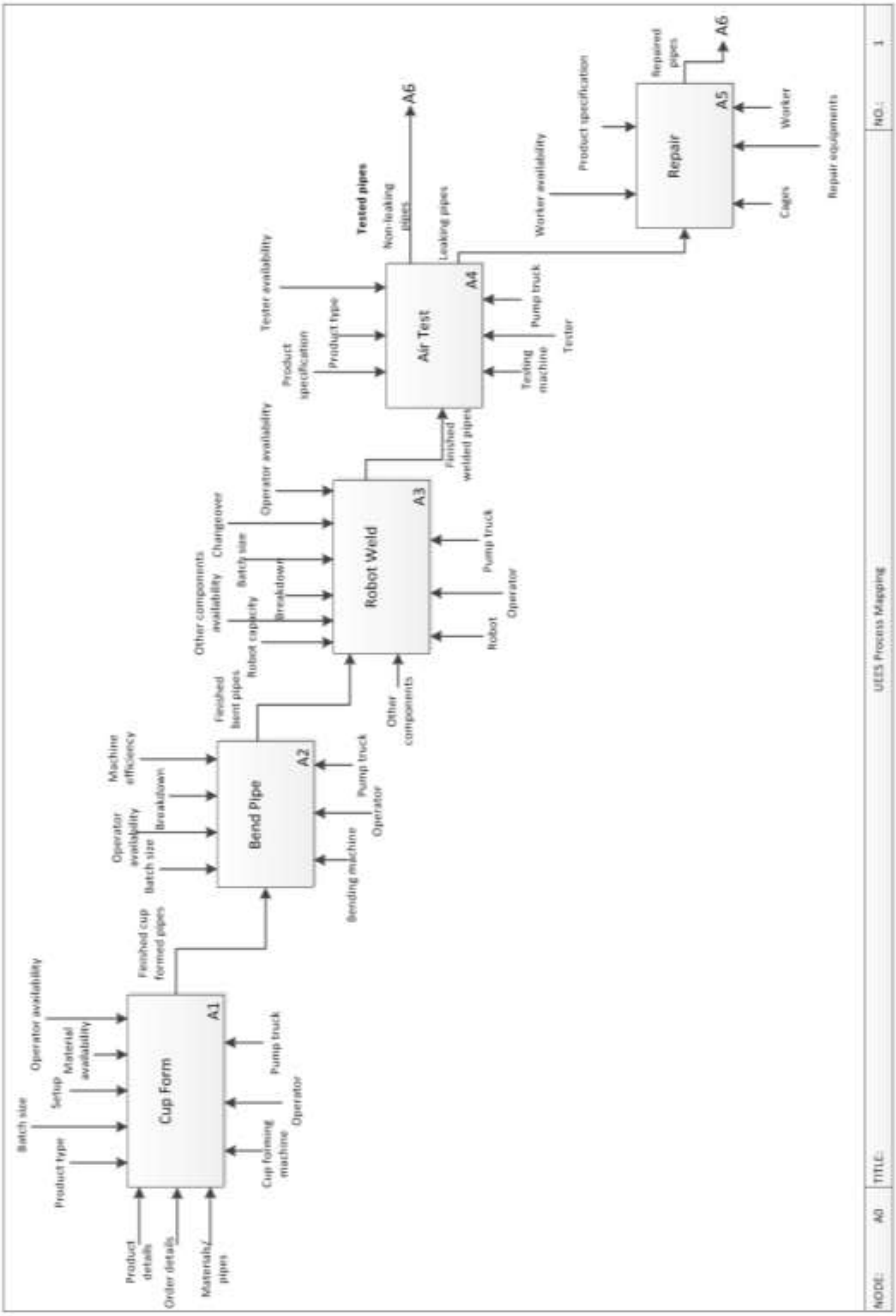


Figure 5-4a: Process Mapping Diagram (IDEF0)

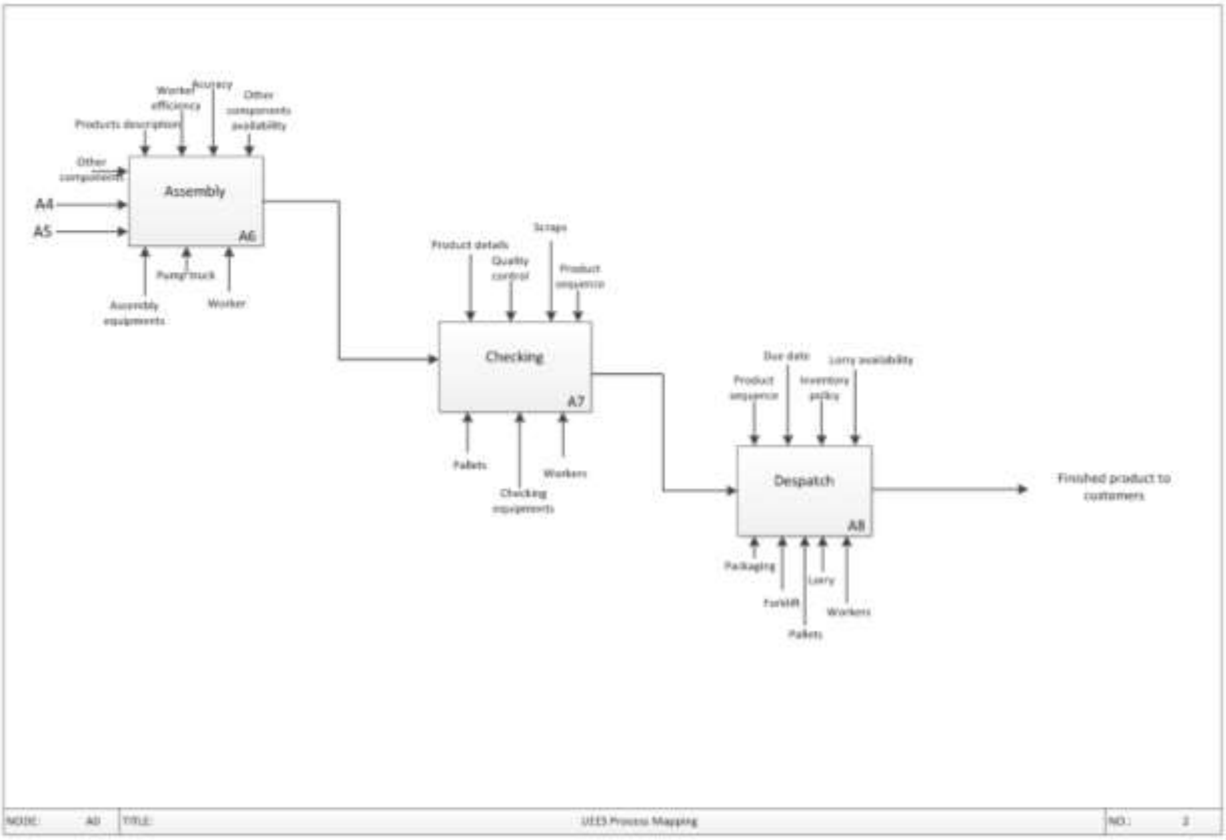


Figure 5-4b: Process Mapping Diagram (IDEF0)

The developed process-mapping diagram is presented to help visualise business processes in terms of each process inputs, which are transformed into output, constraints that control process activities, mechanism that are the physical resources required to complete the process, as well as the output of the process itself. The process flow comprised of the initially discussed eight business processes involved in producing the product type A under review. The processes are bend tube, leg assembly, and robot and seam welding sub assembly, and final assembly process. This is followed by bracket and air test, an inspection process before despatch to customer. Each process involved a set of activities and series of these activities formed the detailed product specific flow shop production of the company.

Based on the process diagram, the production control receives product and order details comprising the product specification, quantity and sequence. This is sent to the flow shop for production to commence. Production batch size is determined, which detailed type and quantity of products to be produced. The first process has an input from the production control: product details and order details, and raw material required for the production. Each process is affected by various restriction including; batch size, set-up, availability of worker, machine breakdown, due date etc. Likewise, there are mechanisms such as workers, pump truck, machines etc. for each process activities to be performed. The output of the first process serves as an input for the next. The despatch process produced an output of finished products sent to customers.

5.6 Single-Product Number Production Explained

As earlier said, the company manufactures five major product families. Each of these product families are sub-divided into different product types which in turn have various product varieties (part number). Fuel filler is a product type with forty-two (42) different part numbers, one of which is FPLA-9032-AC-01 (L405). This part number and other related product family, which are fuel fillers are produced in a designated area, called fuel fillers shown in F5.5 below.

Figure 5-5: Fuel Fillers Production Area

In Figure 5.6, the pipes which are the raw materials to produce fuel fillers are shown. These materials undergo various production processes from raw-material stage to bending, cup forming through to finished product and dispatched.

Figure 5-6: Raw Material (Pipes)

Specifically, a finished fuel filler product number FPLA-9032-AC-01 (L405) undergo the processes that would be explained below.

First, the product raw materials (pipes) are stock in temporary waiting area to be undergoing the first cup forming process. A sticker showing this area is shown in the Figure 5.7 below.

Figure 5-7: Waiting Area

Cup forming: This is where pipes (raw materials) are formed into a cup-like sharp at one end. This is a machine process with process time 'T', carried-out by one worker who operates the machine. This process has machine process time T, for each part as well as number of parts, batch size 'BS' to make at a given period, cycle time 'CT'. The formed parts are checked. Scrap parts are either sent for rework or rejected. The goods one then waits (delay) (waiting time 'WT') in inventory (WIP) before transported to the next process.

Some materials have been removed from this thesis due to Third Party Copyright. Pages where material has been removed are clearly marked in the electronic version. The unabridged version of the thesis can be viewed at the Lanchester Library, Coventry University.

Figure 5-8: Cup-Form Process

Some materials have been removed from this thesis due to Third Party Copyright. Pages where material has been removed are clearly marked in the electronic version. The unabridged version of the thesis can be viewed at the Lanchester Library, Coventry University.

Figure 5-9: Cup-Formed Pipes

Manual transport: Processed cup-formed pipes are transported in cages using pump trunk to the next operation, which is bending pipe. This is carried out by an operator. Transport time 'TT' and distance covered 'DC' are considered.

Bending pipe: This is the process where the cup-formed pipes are bent into the required shapes. This is also a machine process operated by one operator. The machine process time 'T', as well as batch size 'BS' for this operation is also considered here. The bent pipes are checked. Scraps are either rework or rejected before the next process. The goods pipes wait (delay), (waiting time 'WT') in inventory (WIP) shown in Figure 5.12 before transported to the robot welding process.

Figure 5-10: Bending Pipe Process.

The bending pipe operation is carried in bender cell area as shown in Figure 5.11 below.

Figure 5-11: Bender Cell Area

Manual transport: Processed bent pipes are transported in cages using pump trunk to the next operation by a worker. During the process of manually transporting the bent pipes to the next machine, the time of transport and the distance are useful parameters.

Figure 5-12: Bent Pipe WIP

Robot welding: This is an automated process where bent pipes are welded with other parts (brackets, rods, nuts etc.) according to requirement specifications. It is an automated process but operated by one operated. Process time 'T' for each part, changeover/setup time 'CT/ST', and batch size 'BS' as well as machine utilisation 'MU' are parameters to consider. Processed welded pipes (Figure 5.13) are stacked, waiting in inventory (WIP), (waiting time 'WT') and transported, distance covered 'DC' to the next process.

Figure 5-13: Welded Pipe

Air test: This process is where the welded pipes are air-test for leakages. This is also an automated process but operated by an operator. The process time 'T', batch sizes 'BS' are considered as parameters. Successfully welded parts wait (delay) in inventory (WIP), 'WT' and are transported 'DC' to the next process while scraps are taken for rework or rejected (risk of shortage).

Repair: Repair station is the location where scrap parts are rework manually or sent to the appropriate process for machining, rework process time 'RT'. This is carried out by one worker. Repaired parts wait (delay) 'WT' to be joined with the rest of the parts waiting for the assembly operation.

Assembly cell: This is process location where all product-specific parts are assembled, (assembly time 'AT') as finished products. This is a combination of both manual and machine operation (manual process time 'MT' and machine process time 'T'). The finished products are stack in inventory (delay) waiting for final check before dispatched to the customer.

Final check: This is where finished products are quality checked for consistency and accuracy before dispatched. Defective products are rejected for not satisfying requirement and sent for rework (delay) or considered scrap without any rework (waste).

Despatched: This is the final products release to customer(s). Finished products are requires in particular sequence by customer, this sequence is known through hourly demand sticker release to the despatched area by customer. Based on the sticker information, products are then sorted (delay) accordingly to be loaded on the truck for despatched.
The time parameters and bath sizes have been denoted with letters in this report, but the actual parameter will be collected in the cause of the research.

UEES Finished Products

In Figure 5.14, the number of UEES finished products are represented as already stated in section 4.2 above.

(a) Fuel Filler Neck

(b) Fuel Tanks

(c) Engine Components

(d) Diesel Particulate Filters

(e) Exhaust System and Catalytic Convertors

Figure 5-14: The UEES Product Families

For the purpose of illustration, the fuel filler neck (Figure 5.14a) has been selected. The product life cycle of production and the process flowchart of the company products, particularly which represent the fuel filler product family is discussed in the next section.

5.7 Product Life Cycle

The second flowchart in Figure 5.15 represents order handling process. The flowchart begins when new order is received. The order is processed accordingly. A check is carried out to determine if the new order quantity required is less or equal to the current inventory. If it is not, then order process will take place. The system will wait (delay) for the required order quantity to be met. Then sort in demand sequence (delay) if not in sequence until sequence is achieved for demand to be satisfied.

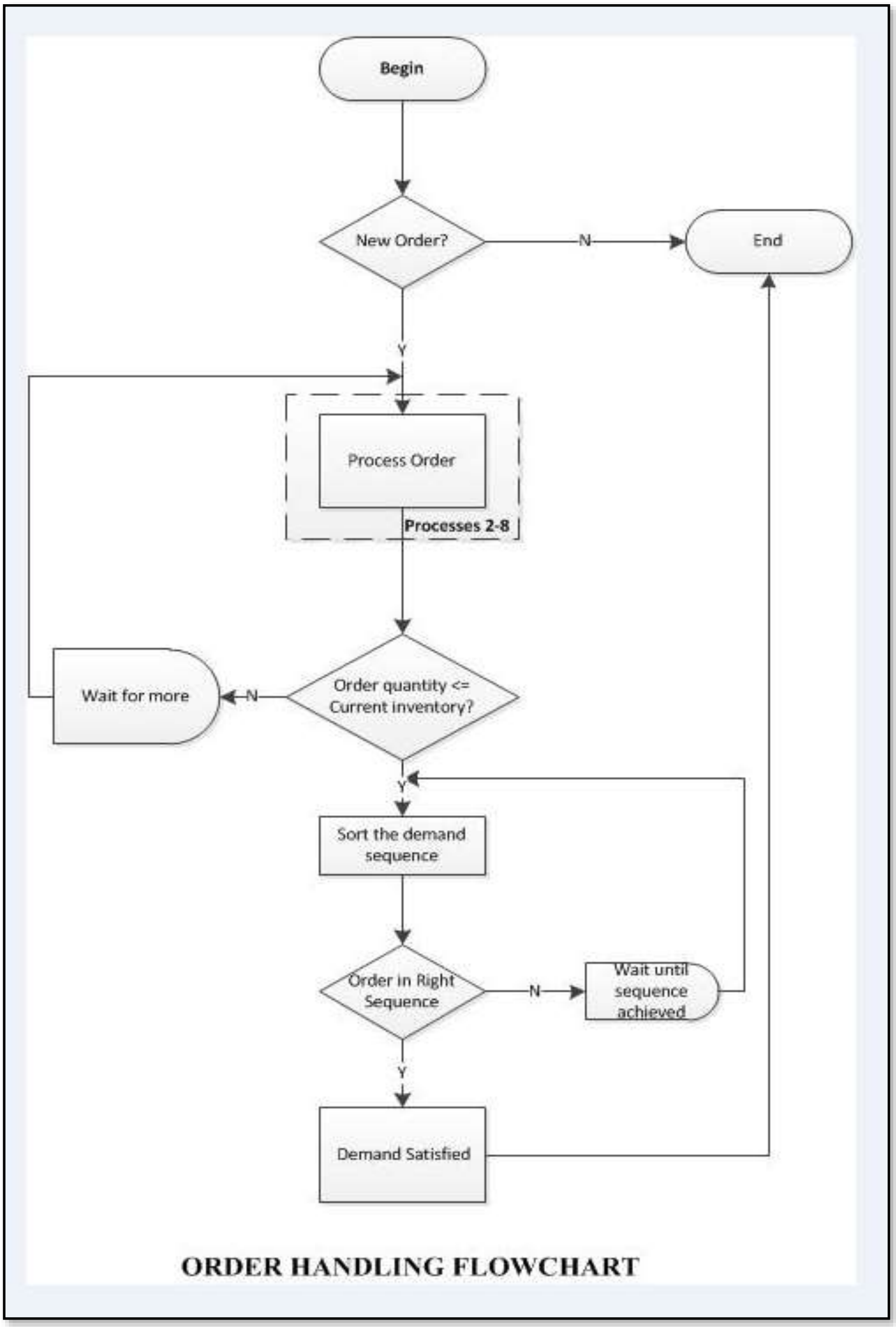


Figure 5-15: Order Handling Flowchart (Product Type A-C).

Two flowchart diagrams are presented, the first one depicts order processing as shown in Figure 5.16 below. Even though the production processes have been earlier explained, it is important to represent them logically using flowchart. This is to enable visualised understanding, decision-making capability within the process and identification of delays and risks involved.

The flowchart starts with demand information. This information effect the check for raw material availability. If raw material is not available to start production, then supplier will be contacted (delay). The system will wait (delay) for materials to be available. Then check for available resource is carried out, if the resources are not available because they are busy, production will wait (delay) to get resource. In the case of available resources and materials, production starts. First process, which is cup forming starts through to the last process, which is checking the products if they meet required specifications. Along the line of operation, queues and inventory (WIP) exists, which is another source of delay. The number of queues and inventory level is best determined by process batch sizes, machine process time, machine availability, setup time and other related parameters. During the final checking process, three decisions are made. Decisions for scrap product, which are sent for rework or rejected (delay and waste). Decision for required quantity, if the products are less than required quantity due to high volume of scraps, then there is a wait (delay) for more to complete demand. Decision for required specification, if the products are not of good quality, they will be sent for rework (delay) or rejected (waste). Likewise, the YES decision products are further checked for right demand sequence. If the products are not in right sequence, they are sorted (delay) to meet the required sequence before finally despatched to customers.

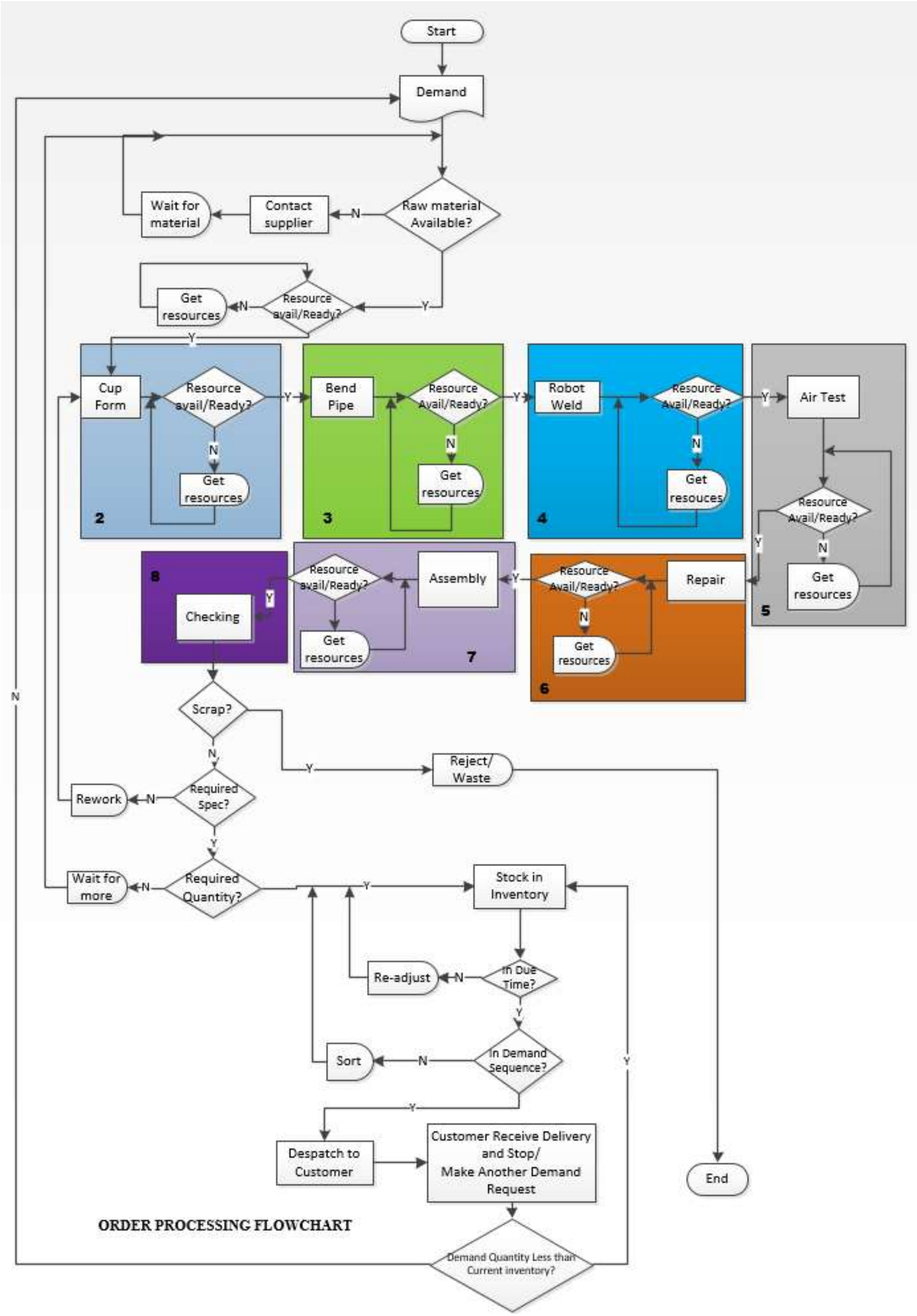


Figure 5-16: Order Processing Flowchart (Product Type A)

5.8 Emerging Production Disruption Problem

In the UEES manufacturing facility, disruption emerges from the day to day production planning and scheduling activities. This type of disruption is called production disruption that is caused by customer changing requirements. In this typical real-life example, customer requirements change in terms of the sequence, time and quantity of orders.

The production disruption that is been studied in this research emerged due to the parallel production relationship that exist between the company and their customers. In this case, orders can be cancelled if problem arise on customer production line. The sequence in which is expected to be delivered might change due time changes in the production line circumstances. Also, certain uncertainties can make customer request for order earlier than expected, which is referred to as change in due time. The combination of these disruption types forms the basis of simulation system development, experimentation and analysis which is been researched in this study.

5.9 Simulation Data Collection

The input data such as order demand and production information are obtained through the real-life case study company (UEES). The data for the research and simulation experiments were collected by visiting the company site, conducting semi-structure interviews, and the use of camera and stop watch.

UEES Site Visit*:* Apart from justifying the identified research problem, production details were obtained through company visits to physically observe the flow shop production layout and environment. The details gathered were used to develop the production flow process, flowchart, IDEF0, flow shop layout diagram that directly represent the production process and flow shop layout which are appropriate to understand the actual real-life manufacturing case study. The visits help the researcher to capture and identify all the operations relevant to the current research.

Semi-Structured Interviews: Apart from establishing the identified research problem, semi-structure interviews were conducted with key personnel within the UEES company site. The interview was semi-structure to allow flexibility when asking questions and giving answers in such a manner that allows additional useful details to be obtained. Although the questions were designed to carefully extract specific information, it further helps in identifying existing production problems as well as establishing the already identified ones. Also, the proposed solution strategy was presented to capture the awareness and appropriateness of it in the real-life industry.

The semi-structure interview was directly to the Production Manager for new business, and some selected experienced flow-shop team leaders and machine operators.

Digital Camera: A digital camera was used to capture photographic data of the company raw materials, work-in-progress, and finished products. Also, the flow shop sections were captured in the photographs as illustrated in the figures in this chapter.

Stop Watch: In as much as the order processing time, machine setup time, and entire production times are essential to the current study, stop watch was used to capture and record these times. The stop watch was used to read and record how long it takes to setup machines, to make a product type, the waiting time, and to fully assemble a finished product. This is instrumental to setting the simulation parameters in this study experiment.

5.9.1 The Flow Shop Information

In this section, the sources of data collection and input parameters for the developed system are highlighted in Table 5.1 and Table 5.2 respectively. Based on the number of simulation scenarios, the data are selected.

Table 5-1: Source of Data

Data	**Method**	**Data Collection Mechanism**
Number of orders	Primary	UEES production sheet
Number of operators	Primary	UEES production sheet

Number of machines	Primary	UEES production sheet
Operational times	Primary	Interviews/ UEES production sheet
Order quantities	Secondary	Third-party customer published order details
Number of orders in inventory	Secondary	Published papers about inventory control

Table 5-2: The system input parameters

Inputs	**Values**	**Units**
Orders	1-30	Number
Order quantities	1-100	Number
Machines	1-30	Number
Operators	1-20	Number
Shifts	1-3	Hours
Production		Days
Inventory	Low, Medium, High	Number
Inventory limit	0-100	%
Setup	Time	Sec/min
Process	Time	Sec/min
Waiting	Time	Sec/min

The input parameters in Table 5.2 shows the values attached to the inputs and their corresponding units. The number of shifts is decided based on the number of order and order quantities. And the inventory limits are selected at random to test the behaviour of the system in respective to the different disruption combination and types.

In Table 5.3, a screenshot of the real-life order, operator and production information is presented as obtained from the case study company (UEES).

Table 5-3: Weekly Real-Life Production Information

L319 MY16

Week No.	Sunday		Monday			Tuesday			Wednesday			Thursday			Friday			Saturday		
	Day	Night	Day	Inter	Night	Day	Inter	Night	Day	Inter	Night	Day	Inter	Night	Day	Inter	Night	Day	Night	
Shift Hours			7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.83	7.68	7.68	7.68			
Perm Headcount			5	3		5	3		5	3		5	3		5	3				
Absence hours																				
Overtime				2		10	6			4		4	6							32
Hours transferred in	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hours transferred out	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Perm Hours Used	0	0	39.15	25.49	0	49.15	29.49	0	39.15	27.49	0	43.15	29.49	0	38.4	23.04	0	0	0	344
Agency Headcount			2	4		2	5		2	5		2	5		2	5				
Absence hours						8														
Overtime				6		4	4			6			6							26
Agency Hours Used	0	0	15.66	37.32	0	11.66	43.15	0	15.66	45.15	0	15.66	45.15	0	15.36	38.4	0	0	0	283.17
Hours used	0.0	0.0	54.8	62.8	0.0	60.8	72.6	0.0	54.8	72.6	0.0	58.8	74.6	0.0	53.8	61.4	0.0	0.0	0.0	
Cumulative Hours	0.0	0.0	54.8	117.6	117.6	178.4	251.1	251.1	305.9	378.5	378.5	437.3	512.0	512.0	565.7	627.2	627.2	627.2	627.2	627.17
Quaff Hours	0.0	0.0	52.8	17.3	0.0	54.8	54.2	0.0	58.7	17.9	0.0	57.6	60.2	0.0	56.2	49.4	0.0	19.0	0.0	
Cumulative Quaff	0.0	0.0	52.8	70.0	70.0	124.8	179.0	179.0	237.7	255.6	255.6	313.2	373.3	373.3	429.6	478.9	478.9	498.0	498.0	497.98
Shift DLP % Performance	0	0	96.3%	27.5%	0	90.1%	74.7%	0	107.1%	24.7%	0	97.9%	80.6%	0	104.6%	80.4%	0	0	0	
Daily DLP % Performance	0			59.5%			81.7%			60.1%			88.2%			91.7%		#DIV/0!		
Cumulative DLP % Perf.	0			59.5%			71.3%			67.5%			72.9%			76.4%		79.4%		
Shift Volume	0	0	157	107	0	164	163	0	176	60	0	170	181	0	167	133	0	31	0	1509
Cummulative Shift Volume	0	0	157	264	264	428	591	591	767	827	827	997	1178	1178	1345	1478	1478	1509	1509	
Target Cost	£0	£0	£822	£269	£0	£853	£844	£0	£914	£279	£0	£896	£937	£0	£875	£769	£0	£296	£0	
Cumulative Target Cost	£0	£0	£822	£1,090	£1,090	£1,943	£2,787	£2,787	£3,701	£3,980	£3,980	£4,876	£5,812	£5,812	£6,688	£7,456	£7,456	£7,753	£7,753	
Actual Cost	£0	£0	£702	£855	£0	£822	£972	£0	£702	£975	£0	£758	£1,006	£0	£688	£363	£0	£0	£0	
Cumulative Actual Cost	£0	£0	£702	£1,557	£1,557	£2,379	£3,351	£3,351	£4,053	£5,027	£5,027	£5,785	£6,791	£6,791	£7,479	£7,842	£7,842	£7,842	£7,842	
Shift Cost Varience	£0	£0	£120	-£586	£0	£31	-£128	£0	£212	-£696	£0	£138	-£69	£0	£187	£406	£0	£296	£0	
Cost Varience To date	£0	£0	£120	-£466	-£466	-£436	-£564	-£564	-£352	-£1,048	-£1,048	-£909	-£978	-£978	-£791	-£385	-£385	-£89	-£89	
Part Number	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	Qty	TOTAL
GH22-5K244-AD			53			52	50		55			61	55		57	52		31		466
GH22-9N497-BB			53	72		52	50		55			61	55		57	33				488
GH22-9N497-CD			51	35		60	63		66	60		48	71		53	48				555
																				0

From the information obtained (Table 5.3) for the UEES, the system input parameters were set to directly mimic the real-life scenario. The table shows the weekly production period including, shift hours for three daily shifts (day, inter and night shifts) with 7.83 hours per day (excluding breaks); operators per day and overtime hours; performance per shift and per day; and the number of order (parts) quantities per shift per day. It also reveals the total number of order quantity for the weekly production period.

5.10 Verification and Validation of the Proposed System

The verification and validation of the proposed system is done using several techniques. This section details the steps taken to verify the system is as expected and validate the system fit for purpose to which it has been developed.

5.10.1 Verification of the Proposed System

Before developing the system, all the designed logics, system specification and flow processes, and production activities were presented to the experienced experts in the case study company. The experts, production and operation managers at UEES, reviewed and confirmed the appropriateness of the presented designs and specifications for the proposed system. Simulation procedures for the flow shop production were printed in the system profiles including input parameter, and flow shop layout, flowcharts and UML diagrams as well as entity relational representation of the simulation system. Also, different operational time calculation was checked for acceptability with the existing real system. Some of the system profile and pictorial illustration presented for verification were discussed in Chapter 4.

5.10.2 Validation of the Proposed System

The proposed system was validated by determining if the output of the system is close to reality. Using the validation procedure, the simulation results were checked with the real-life system under the same parameters. The validation procedure was used to follow through a specific order production. An order with order quantity of 45 with 100% inventory level on a single shift. The order production flows through all 5 process stations until completion using 9 operators. The average total process time is 432 mins with the average resource performance rate at 90.1% for machines, 80.6% for operators and the total idle time 45 mins. The production time, setup time, process time, resource utilisation, idleness and waiting time were all checked for their closeness to reality. In some cases, time variations occurred which was as result of simulation time randomness. However, as this does not deviate significantly from the real-life results, they were accepted by the company experts as a valid results.

Chapter 6: Experimentations, Results Analysis and Discussions.

6.1 Introduction

This chapter presents the results of the OEMs flow-shop production experimental work conducted based on the three production disruption scenarios. It includes the analysis and discussions of different scenarios results and the comparison of the proposed heuristic approach with the current situation "As-Is" and other approaches. The chapter focuses on the impact of disruption on flow-shop and the behaviour of inventory support, the replenishment plan and the resources utilisation at different instances, which formulates key area of discussion. The performance of the type of heuristic algorithm proposed in this study is verified by the computational experiments presented in this chapter. The experiments consider the three customer-imposed disruptions types emphasised in this study, under different order volumes, order quantities, inventory status, and working shifts. The further details of the real-life flow-shop information applied in the experiment is discusses in Section 5.9.1 of Chapter 5 of this thesis.

The chapter is organised as follows; disruption scenario experiments illustrated with result tables and graphs, production key performance indicators (KPIs) in terms of resource (operator-machine) utilisation and utilisation comparison, number of late/unsatisfied orders, overall inventory behaviour analysis and comparison, heuristic approach comparison with other approaches and concluded with chapter summary.

6.2 Production Disruption Experiment Scenarios

The scenario experiments were conducted each with random combination of the three types of disruptions. In the appendix, the disruptions tables are presented for all scenarios. For each disruption combination, different demand volume and inventory status were considered for experimentation based on the following scenario combinations;

- High order volume vs Full inventory level (HF).
- High order volume vs Safe inventory level (HS).
- High order volume vs Critical inventory level (HC).
- Average order volume vs Full inventory level (AF).
- Average order volume vs Safe inventory level (AS).
- Average order volume vs Critical inventory level (AC).
- Low order volume vs Full inventory level (LF).

- Low order volume vs Safe inventory level (LS).
- Low order volume vs Critical inventory level (LC).

The High, Average and Low order volumes scenario of order number ranges of 100-120, 40-60, and 10-20 orders respectively. And the order quantity range between 80-100 for High, 40-50 for Average and 20-25 for Low order volumes. Each scenario was considered under Full (100), Safe (50), and Critical (10) inventory level conditions. For High order volume scenarios, 3 shifts pattern was set, 2 shifts pattern for Average order volume while a single shift for Low order volume as follow.

- Shift 1: 00:01 - 08:00.
- Shift 2: 08:01 - 16:00.
- Shift 3: 16:01 - 23:58.

The range of order volume has been selected to replicate the real-life production order range. The order quantity range has been set to maintain a controlled variation with the three levels inventory status considered in the experiments. The number of shifts is assigned corresponding to the order volumes. The High, Safe and Critical inventory levels are set to understand production behaviour under the three inventory categories. The selected shift patterns mimic the real-life system operation and it is corresponding to the demand volume.

6.2.1 Justification for the combining the three disruption types.

The three types of disruptions occur daily and randomly in real life OEMs production system. Selecting any of these disruption types on its own for consideration can be bias. Since, no disruption type is anticipated or expected per day for the entire production period (PP) in reality. Therefore, the disruption types are given equal chance to naturally occur individually and/or combined. However, individual disruptions experiments scenarios are presented in the appendix section of this report. They were tested and presented to further learn and understand the behaviour of the system if disruption were to occur individually.

In each of the presented scenarios, three order samples were selected randomly for analysis and discussion. This is to present a replica, clearer and better understanding of the inventory replenishment concept explained in Section 3.5 of Chapter 3, through discussion. Most importantly, it is essential to prevent inconsistency in explanation which might create confusion while bringing the theoretical perception to live through real experimentation.

6.3.1 High order vs Full inventory

This scenario studies the effect of disruptions on flow-shop operation when there are high order volumes and full inventory levels. Table 6.1 presents the results of the first selected order type which highlights the production progress over 20 days production period. The table is based on the demand quantities before and after disruptions, the actual production with inventory support, inventory borrow, inventory level daily and the late/unsatisfied orders. The tables presented in the following experiments not only refer to the cancellation disruption but all combined. However, cancellation disruption is the only disruption that is directly dependent on quantities. Therefore, the visible impacts of all disruptions on demand, production, replenishment, borrow, inventory and late order quantities have been shown through the tables. The colours "blue", "orange", "green" and "red" of some highlighted cells denote "replenishment", "inventory", "cancellation", and "late/unsatisfied orders" respectively. These directly illustrate the days and parameters affected by disruptions as well as the effect on the corresponding parameters of the highlighted cells in terms of order quantities.

Table 6-1: First selected order results table for high order volume vs full inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		88	85	100	95	85	93	99	81	90	80	84	97	81	90	88	92	81	89	82	96
Demand After Disruption		88	35	85	72	45	93	99	81	64	80	84	97	81	90	50	72	81	89	82	96
Actual Production		88	35	80	72	40	55	60	60	55	76	42	80	81	60	45	42	35	75	82	60
Production PLUS Replenishment		88	35	80	72	40	55	60	60	55	104	42	80	126	60	45	42	35	75	132	60
Borrow		0	0	5	0	5	38	39	13	0	4	24	0	0	30	5	10	0	0	0	36
Replenishment		0	0	0	0	0	0	0	0	0	28	0	0	45	0	0	0	0	0	50	0
Inventory	100	100	100	95	95	90	52	13	0	0	24	0	0	45	15	10	0	0	0	50	14
Cancellation		0	50	15	23	40	0	0	0	26	0	0	0	0	0	38	20	0	0	0	0
Production with Inventory Support		88	35	85	72	45	93	99	73	55	80	66	80	81	90	50	52	35	75	82	96
Late/Unsatisfied orders		0	0	0	0	0	0	0	8	9	0	18	17	0	0	0	20	46	14	0	0

Over the 20 days production period, initial order quantity (demand) range from 80 to 100 per day of 100 different order types are generated. From the table, it can be observed that there are number of order cancellation (indicated in green colour) from the first selected order. Order cancellation disruption is significant to quantity of order as it reduces the quantity of initial order. Cancellation of this order occurred on days 2, 3, 4, 5, 9, 15 and 16 which reduces the initial quantities now called the demand after disruptions. The production flow-shop managed to produce the same number of orders after disruptions until day 3 based on capacity and resources utilisation. On day 3, fewer number of orders after disruptions were produced, prompting inventory support for 5 remaining order quantity reducing inventory level to 95. From day 5 to 8, inventory level continues to diminish to zero as more support (borrow) were required to complete demand due to disruptions. As inventory level remain zero, unsatisfied orders were recorded on day 8 and 9. This was because there are continuously fewer number of order production and no inventory to support. Similar occurrence on days 16, 17 and 18 before inventory replenishment of 50 orders on day19 are noticed. Two order instances of replenishments occurred on days 10 and 13, as instructed though the proposed heuristic. Although there are cancellation of order in some of the days listed above, there are still instances of borrow from the inventory. This is because change in sequence and due time disruptions also cause delay in production which makes the actual production lower than the demand after disruption. For instance, on day 3 where 15 orders was cancelled from the demand of 100 orders dropping to 85 orders after disruptions, the actual production was 80 orders. This results into 5 orders borrow from inventory to satisfy demand. Apart from disruption occurrences, resources (machines and operators) availability are key factors affecting number of production.

Additionally, Figure 6.1 reveals the demand production graph and the inventory replenishment plan for the first selected order below.

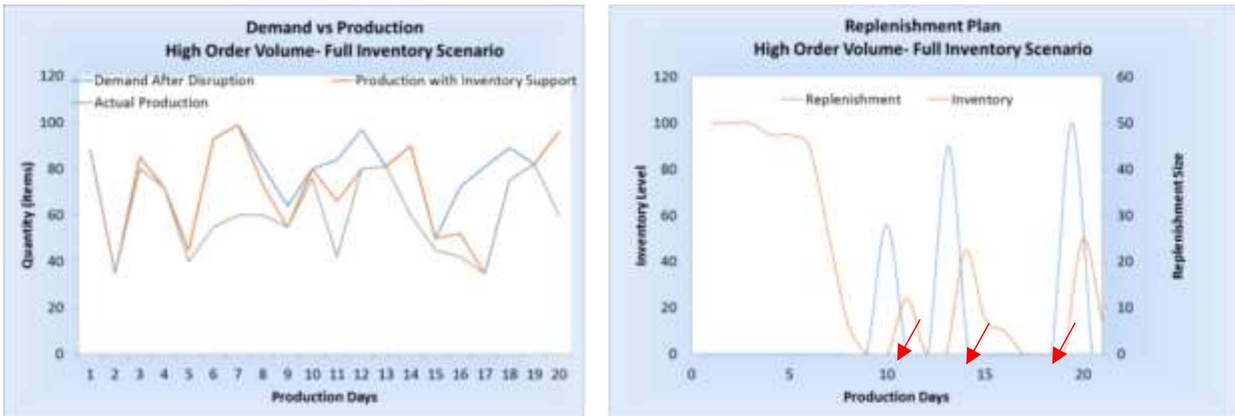


Figure 6-1: a) First selected order demand and production for high order volume vs full inventory level. b) First selected order replenishment plan for high order volume vs full inventory level

From the demand production graph, the higher demand after disruption against the actual production begin to be noticeable from day 5 as production drops. The irregular trends of the three key indicated factors (demand after disruptions, actual production, and production with inventory support) shows the disruptive state of the flow-shop and how the system manage to respond. It is reflected through the continuous reduction of the inventory used for production support during disruptions. The three instances of inventory replenishments came at the point where inventory level was zero as indicated by the arrows. This satisfied one of the proposed heuristic rules that give replenishment priority to order at the least level when other rules are satisfied. Although the inventory borrow supports production and minimise the number of unsatisfied orders, in some days the continuous disruptions occurrences in conjunction with resources utilisation and availability drastically prevent enough production, as it is the case on days 8, 9, 11, 16, 17 and 18. In situation like when the inventory becomes unsupportive at critical or zero level, it results into late/unsatisfied order in those 6 day. The replenishment graph rise to the level corresponding to the order quantity been replenished on the day(s) where there is any available time for replenishment.

In Table 6.2, the production results for the second selected order is presented showing the demand, demand after disruption, actual production, borrow, replenishment, inventory level and number of late/ unsatisfied quantity of the second selected order.

Table 6-2: Second selected order results table for high order volume vs full inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		98	86	80	81	86	83	89	91	99	84	96	87	89	95	87	84	96	85	87	94
Demand After Disruption		98	86	60	69	86	83	89	66	99	84	96	87	89	0	87	84	96	85	87	64
Actual Production		60	65	60	60	75	83	89	66	80	66	80	0	80	0	87	68	90	68	60	52
Production PLUS Replenishment		60	65	60	60	75	107	94	66	80	66	80	0	80	62	87	68	90	68	60	52
Borrow		38	21	0	9	11	0	0	0	19	18	13	0	0	0	0	16	6	17	23	0
Replenishment		0	0	0	0	0	24	5	0	0	0	0	0	0	62	0	0	0	0	0	0
Inventory	100	62	41	41	32	21	45	50	50	31	13	0	0	0	62	62	46	40	23	0	0
Cancellation		0	0	20	12	0	0	0	25	0	0	0	0	0	95	0	0	0	0	0	30
Production with Inventory Support		98	86	60	69	86	83	89	66	99	84	93	0	80	0	87	84	96	85	83	52
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	3	87	9	0	0	0	0	0	4	12

This selected order has 5 instances of cancellation on days 3, 4, 8, 14 and 20, which reduce the number of initial demand quantities. The disruptions occurrence begins to drop production from the first day of production. Out of the 98 orders requested on day 1, 60 were produced, requiring 38 orders borrow from inventory. On day 2, 65 orders were produced out of 86 requested, further requiring 21 order support from inventory to complete production. The inventory level reduces on the first two days but remained stable from days 2 to 3. This is because the number of productions is equal to the demand after disruption. From day 6 when production start to improve, there was equally inventory replenishments on days 6 and 7 raising inventory level from 21 to 50. This increase the supporting strength of the inventory which was utilised on days 9 and 10 when production drops again. The effect of disruptions was revealing on days 11, 12 and 13 where collective high number of unsatisfied orders were recorded. This was also because of lack inventory to support zero production on day 12. Even though there was high replenishment of 62 orders on day 14, it was exhausted in three days of no further replenishment but continuous borrow. So, late/unsatisfied orders were recorded on days 19 and 20. Apart from the impact of disruptions on production, machines availability, functionality and capacity; operators' skills and availability are collectively significant to actual production. This explains the fluctuations experience in actual production quantities.

In Figure 6.2, the pictorial representation of the demand production and inventory replenishment plan are presented.

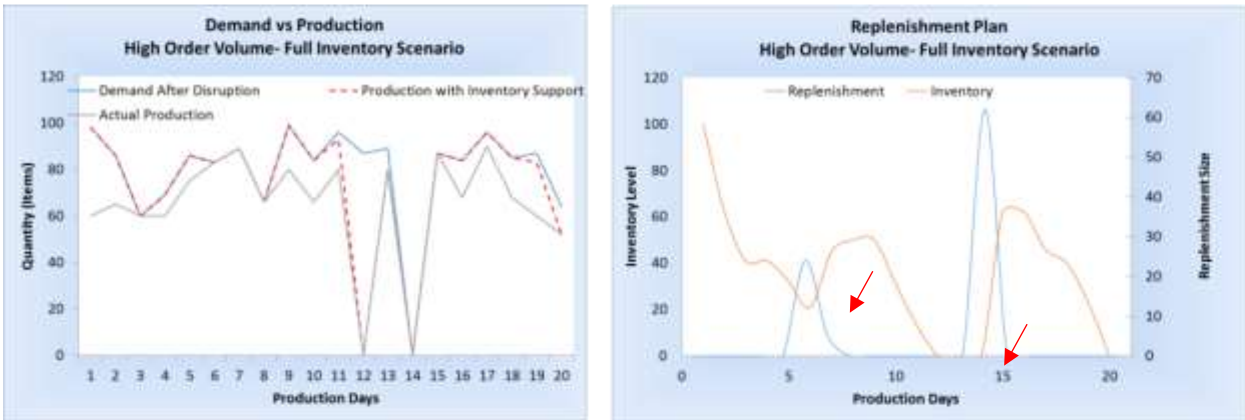


Figure 6-2: a) Second selected order demand and production for high order volume vs full inventory level. b) Second selected order replenishment plan for high order volume vs full inventory level

On the demand production graph in figure 6.2a, demand after disruption is seen supported by inventory even though actual production drops. The support continues until order in inventory was exhausted on day 11. This indicates why demand after disruption is higher than both actual production and production with support. In this situation, late/ unsatisfied orders increase in number as it is the case on day 12. Also, day 12, there was no production for the requested 87 orders. With no order left in the inventory, this brings the entire daily order to be completely unsatisfied. On the replenishment plan in figure 6.2b, there are only three instances of replenishment on days 6, 7, and 14 which increase the level of inventory. This is because order replenishment happens only when there is available time and resources at a given time. And most importantly replenish is done when inventory level of any order is below their "100%" level, that is, when they are critical, average or safe levels, irrespective of production day. The availability of inventory support also reduces the impact of disruptions by minimising the number of late/unsatisfied orders.

In general, it appears inventory continually support production shortages when there are disruptions. However, in some cases such as limited availability of resources such as operators and machines lead to lower productivity which reduces the number of replenishment and leave some orders late/unsatisfied.

In Table 6.3 below, the third selected order results are displayed indicating the production information like the first two selected orders.

Table 6-3: Third selected order results table for high order volume vs full inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		81	82	95	84	86	97	93	84	86	82	99	100	87	86	91	97	86	88	100	83
Demand After Disruption		0	22	39	84	86	97	93	84	86	82	99	75	87	86	91	97	86	88	0	83
Actual Production		0	22	39	73	80	91	75	70	78	60	60	75	70	70	56	88	50	72	0	75
Production PLUS Replenishment		0	22	39	73	80	91	75	70	78	60	60	75	70	70	56	88	50	72	50	75
Borrow		0	0	0	11	6	6	18	14	8	22	15	0	0	0	0	0	0	0	0	8
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0
Inventory	100	100	100	100	89	83	77	59	45	37	15	0	0	0	0	0	0	0	0	50	42
Cancellation		81	60	56	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	100	0
Production with Inventory Support		0	22	39	84	86	97	93	84	86	82	75	75	70	70	56	88	50	72	0	83
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	24	0	17	16	35	9	36	16	0	0

The initial demand of this order dropped to zero after cancellation disruption on two occasions; days 1 and 19. On the first 3 days where production was equal to the demand after disruption, inventory level remained constant. The level of inventory begins to drop from day 4 when the quantity of order production reduces until day 11. During this period, the effect of disruption does not impact the demand satisfaction. This is because inventory support is enough. However, on day 11, 24 orders were recorded as unsatisfied since inventory quantity is exhausted. With further disruptions and no inventory replenishment from day 12 to 18, many unsatisfied orders were recorded.

In Figure 6.3, the impact of disruptions on the third selected order is shown on demand production and inventory replenishment plan.

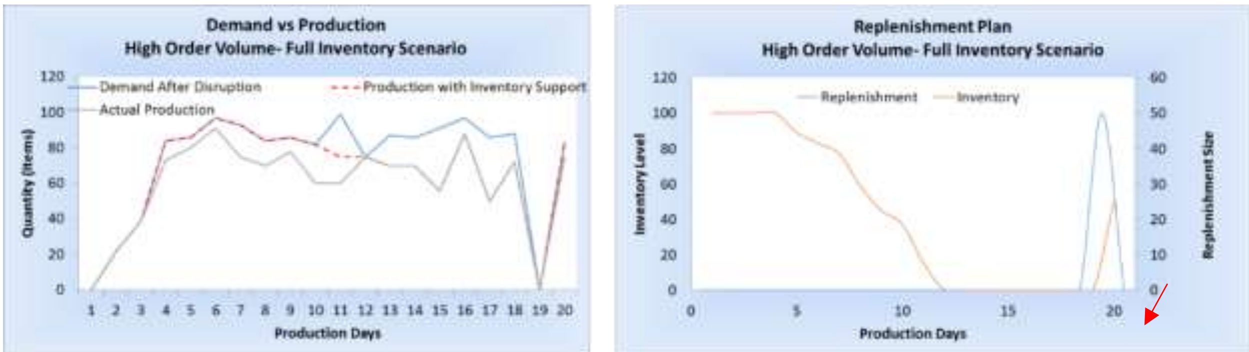


Figure 6-3: a) Third selected order demand and production for high order volume vs full inventory level. b) Third selected order replenishment plan for high order volume vs full inventory level.

Disruption was adapted for the first 10 days of production where all order demand after disruption were fully satisfied with borrow from the inventory. However, as the actual production continues to decline, inventory level drops accordingly. As the support from inventory stops, days of late/unsatisfied orders increased from day 13 to 18. This is indicated with higher demand after disruption against actual production without inventory support.

The higher number of late/unsatisfied orders was recorded since there is no more support from inventory due to low productivity and limited number replenishment. In Figure 6.3b, the inventory replenishment trend implies that there are no enough inventory supports to completely adapt to the order shortages caused by disruptions. Only one instance of replenishment can be observed on day 19 when inventory was at zero level. There was no replenishment from day 11 even when inventory level drops to zero. This is because there was no evidence of available time, machines and operators at the same time during this period of days 11 to 18.

Judging by the number of order completion, disruption caused a high number of unsatisfied orders with high volume and full inventory. Even though there are instances of replenishments through the available time created by the cancellation disruption, the inventory is still not sufficient to completely satisfy customer demand. From the three selected orders, there are high number of unsatisfied orders. This showed that the impact of disruptions is high on production with high order and full inventory. The three orders are randomly selected from each of the experiments conducted for the purpose of illustration. For each experiment, three different random orders are selected among the orders results that are significantly impacted by the disruptions and demonstrate the effect of the proposed solution in this research. They reveal critical points of interest for discussion and analysis.

The replenishment plan has been correctly executed based on the current level of individual order inventory at the time of replenishment. The effect of disruptions on the demand production is corresponding to order inventory levels. In this scenario, the flow-shop experience shortage when disruptions set in. However, these disruptions do not have much effect on demand satisfaction until inventory level becomes insufficient to support production. For example, on day 11 of order 3, the number of demands after disruption become higher than the production with inventory support because inventory level reads zero on this day. Consequently, customer orders cannot be completed and are recorded as late or unsatisfied orders.

The three orders scenario was selected to reflect the impact of the proposed heuristic rule for inventory replenishment strategy. At each point of replenishment, the order with the least inventory was selected for replenishment. This demonstrates the gradual non-instantaneous replenishment strategy described in Section 3.5 of Chapter 3. The strategy makes it possible for the system to concentrate on balancing inventory levels of all orders. This is to enhance continuous support for production shortages in a sustainable manner.

6.3.2 High order vs Safe inventory

This scenario experiment studies the effect of disruptions on production flow-shop when there are high order volume and safe inventory level. This high order indicates order range from 80 to 100 while safe inventory is inventory level of 50. In Table 6.4 the results of the first order selected is presented. The table shows the number of the first order quantities demanded over a period of 20 days and the production activities.

Table 6-4: First selected order results table high order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		80	89	100	81	90	81	96	87	92	97	81	80	88	96	100	85	83	85	85	100
Demand After Disruption		80	89	100	81	90	81	28	87	92	52	0	80	88	96	100	85	83	85	0	100
Actual Production		80	80	80	81	75	70	28	68	70	52	0	68	85	70	85	50	58	42	0	90
Production PLUS Replenishment		80	80	80	81	75	70	58	68	70	77	12	68	85	70	85	50	58	42	28	90
Borrow		0	9	20	0	15	6	0	19	11	0	0	12	3	22	0	0	0	0	0	10
Replenishment		0	0	0	0	0	0	30	0	0	25	12	0	0	0	0	0	0	0	28	0
Inventory	50	50	41	21	21	6	0	30	11	0	25	37	25	22	0	0	0	0	0	28	18
Cancellation		0	0	0	0	0	0	68	0	0	45	81	0	0	0	0	0	0	0	85	0
Production with Inventory Support		80	89	100	81	90	76	28	87	81	52	0	80	88	92	85	50	58	42	0	100
Late/Unsatisfied orders		0	0	0	0	0	5	0	0	11	0	0	0	0	4	15	35	25	43	0	0

For the first selected order, initial order quantity was reduced due to cancellation which occurred on four occasions. In two of the order cancellation days; days 11 and 19, the initial orders were completely cancelled. The cases of complete cancellation of order leave room for available time slots which are used for inventory replenishments. Where there was also machines and operators available, the replenishment occurred on days 7, 10, 11, and 19. However, when there was no replenishment and inventory become zero, late/unsatisfied orders were recorded on days 14 to 18. The situation also occurs on day 6 and 9 where the number of actual productions is not enough to satisfy the demand after disruptions, but inventory level was zero.

In Figure 6.4 below, the demand production and inventory replenishment plan of the first selected order is represented.

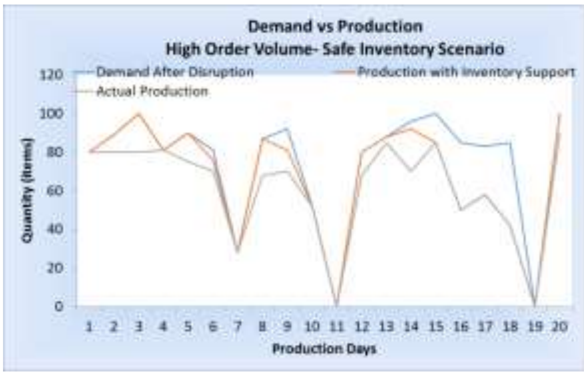


Figure 6-4: a) First selected order demand and production for high order volume vs safe inventory level. b) First selected order replenishment plan for high order volume vs safe inventory level.

The support for production shortage to prevent late/unsatisfied orders is evident from day 2 until day 5 when inventory level became zero. However, on days 7, 10 and 11, there was replenishments and continuous inventory support which eradicate late/unsatisfied orders before inventory went back to zero level on day 14. The production period where shortage and lack of support was experience on the production flow-shop is shown by the demand after disruption trend which is clearly higher than production. In Figure 6.4b, there are three instances of replenishments which explain why inventory was increased to further support production shortages. The level of inventory in this scenario is not always enough to support production, especially when production continually drops over a longer period of days as it is the case on days 14 to 18.

In the Table 6.5 below, the second selected order results are represented showing key flow-shop production activities.

Table 6-5: Second selected order results table high order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		84	87	91	98	95	96	85	87	90	95	97	82	84	95	91	85	97	100	88	96
Demand After Disruption		84	87	91	0	95	96	85	87	90	95	97	82	84	95	21	85	97	100	88	96
Actual Production		84	84	65	0	71	85	85	87	90	95	87	80	78	95	21	85	90	100	87	78
Production PLUS Replenishment		84	84	65	20	71	85	85	87	90	120	87	80	78	95	21	85	90	100	87	78
Borrow		0	3	26	0	24	11	0	0	0	0	10	2	6	0	0	0	7	0	1	5
Replenishment		0	0	0	20	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0
Inventory	50	50	47	21	41	17	6	6	6	6	31	21	19	13	13	13	13	6	6	5	0
Cancellation		0	0	0	98	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0
Production with Inventory Support		84	87	91	0	95	96	85	87	90	95	97	82	84	95	21	85	97	100	88	83
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13

The effect of disruption on the second selected order is minimal even with safe inventory scenario at high order demand. This is can be explained by high productivity level of the second order during the entire production period. The number of demands after disruption is most of the time equal to the actual production. Whenever the demand is more than the actual production, it is minimal, and inventory is available to support the shortages. As a result, there was not issue of late/unsatisfied order until day 20 when inventory become zero with no replenishment. The sustainability of the inventory in the scenario is also due to enough replenishment that occurred to increase the inventory level on two occasions. In Figure 6.5, the demand production and inventory replenishment plan for the second selected order is shown.

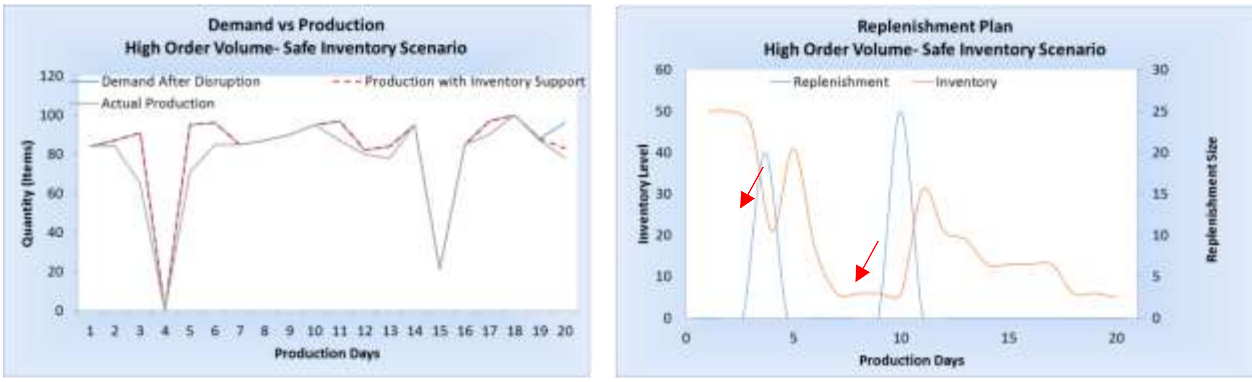


Figure 6-5: a) Second selected order demand and production for high order volume vs safe inventory level. b) Second selected order replenishment plan for high order volume vs safe inventory level.

The support from the inventory is evident from the trend throughout the production period until day 20.

Table 6-6: Third selected order results table high order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		85	99	97	86	94	87	95	92	99	96	86	94	97	88	82	95	93	97	92	90
Demand After Disruption		85	55	97	86	94	87	95	92	99	96	86	94	97	88	82	95	48	82	0	90
Actual Production		68	55	90	86	90	78	84	92	98	90	75	87	80	80	82	91	48	75	0	55
Production PLUS Replenishment		68	65	90	86	90	78	84	92	98	90	75	87	80	80	98	91	48	75	10	55
Borrow		17	0	7	0	4	9	11	0	1	6	5	0	0	0	0	4	0	7	0	15
Replenishment		0	10	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	10	0
Inventory	50	33	43	36	36	32	23	12	12	11	5	0	0	0	0	16	12	12	5	15	0
Cancellation		0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	15	92	0
Production with Inventory Support		85	55	97	86	94	87	95	92	99	96	80	87	80	80	82	95	48	82	0	70
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	6	7	17	8	0	0	0	0	0	20

Figure 6.6 represent the demand production trend with the inventory replenishment plan. It is the graphical representation of table 6.6.

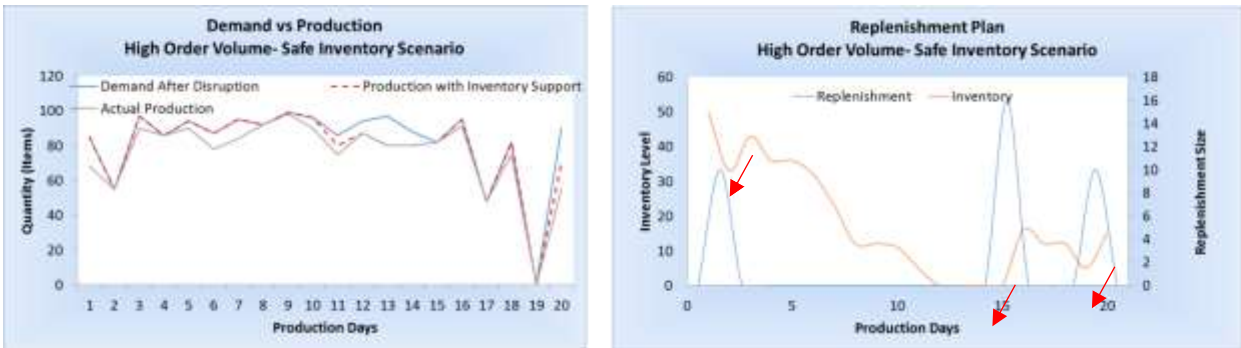


Figure 6-6: a) Third selected order demand and production for high order volume vs safe inventory level. b) Third selected order replenishment plan for high order volume vs safe inventory level.

The consequences of disruption on production has more effect with safe inventory level when the demand volumes are high. This is because inventory support was exhausted within the first

4 days as the case of Table 6.6. However, the situation is continually rescued with replenishments implementation and effective resource utilisation (discussed in sections below). For instance, in Table 6.4 production drops due to disruptions from day 2 to day 5. For this reason, inventory level drops in response to supporting production against order shortages. However, there were replenishment on days 7, 10 and 11 where inventory was topped up which help reduce the number of unsatisfied orders.

It can be deduced that the more disruptions causing replenishment, the less the number of unsatisfied orders as there would be support for production even when demand after disruptions is higher than actual productions. The situation in table 6.5 is different from Table 6.6 and Table 6.4, because number of actual productions is almost equal to the demand after disruption and so inventory level was sustainable until day 20 when 13 unsatisfied order was recorded.

The interesting impact of disruptions for the three selected orders production are the drastic drop in the inventory levels. This happens in such a way that tends inventory levels towards zero. However, an intermittent rise of the inventory level, as the case of 6.5 and 6.6, came due to replenishment occurrences. The interesting part is that it is the effect of disruption such as cancellation that created was it referred to as ‘available time slots’ in this study, which are then utilised for inventory replenishment. This is an example of the system demonstrate an adaptive way of responding to disruptions by taking advantage of its consequences as one of the key solution strategies.

6.3.3 High order vs Critical inventory

This section presents the effect of disruption on production when there are high order volumes but critical inventory level available for support. Table 6.7, 6.8 and 6.9 display results of three selected orders in this scenario.

Table 6-7: First selected order results table high order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		80	89	100	81	90	81	96	90	82	87	91	90	98	86	80	95	93	95	83	80
Demand After Disruption		80	89	100	81	90	81	28	90	82	77	91	90	98	86	75	95	93	95	83	80
Actual Production		80	80	80	81	75	70	28	78	60	77	80	78	85	60	68	60	74	68	0	61
Production PLUS Replenishment		80	80	80	81	75	70	28	78	60	82	80	78	85	60	68	60	74	68	0	61
Borrow		0	9	1	0	0	0	0	0	0	0	5	12	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	1	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Cancellation		0	0	0	0	0	0	0	0	0	10	0	0	0	0	5	0	0	0	0	0
Production with Inventory Support		80	89	81	81	75	70	28	78	60	77	85	78	85	60	68	60	74	68	0	61
Late/Unsatisfied orders		0	0	19	0	15	11	0	12	22	0	6	12	13	26	7	35	19	27	83	19

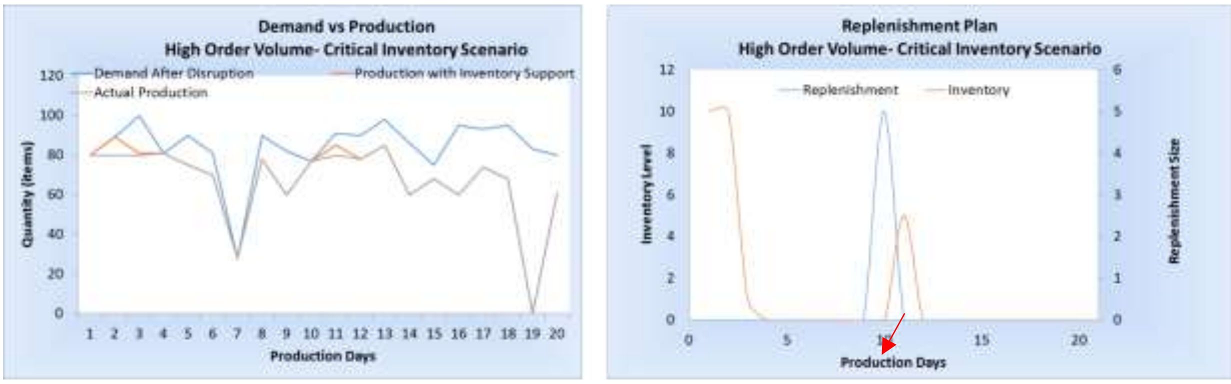


Figure 6-7: a) First selected order demand and production for high order volume vs critical inventory level. b) First selected order replenishment plan for high order volume vs critical inventory level.

As shown in Figure 6.7, 6.8, and 6.9, the level of inventories for the three order types were zero for most of the production period. This is because there are more demands after disruptions than the system can produce and for inventory to support. Although in Figure 6.9, there are two instances of replenishment, but the inventory level limit is critical and make little difference considering the high demand volumes.

Table 6-8: Second selected order results table high order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		94	97	81	88	85	86	84	87	95	96	92	84	80	100	81	95	93	100	98	92
Demand After Disruption		94	97	60	88	85	86	84	87	95	96	92	84	80	100	81	95	93	0	18	0
Actual Production		94	97	60	60	81	65	74	87	82	95	80	80	68	95	40	85	64	0	18	0
Production PLUS Replenishment		94	97	60	60	81	65	74	87	82	95	80	80	68	95	40	85	64	10	18	0
Borrow		0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
Inventory	10	10	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	10
Cancellation		0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	80	92
Production with Inventory Support		94	97	60	70	81	65	74	87	82	95	80	80	68	95	40	85	64	0	18	0
Late/Unsatisfied orders		0	0	0	18	4	21	10	0	13	1	12	4	12	5	41	10	29	0	0	0

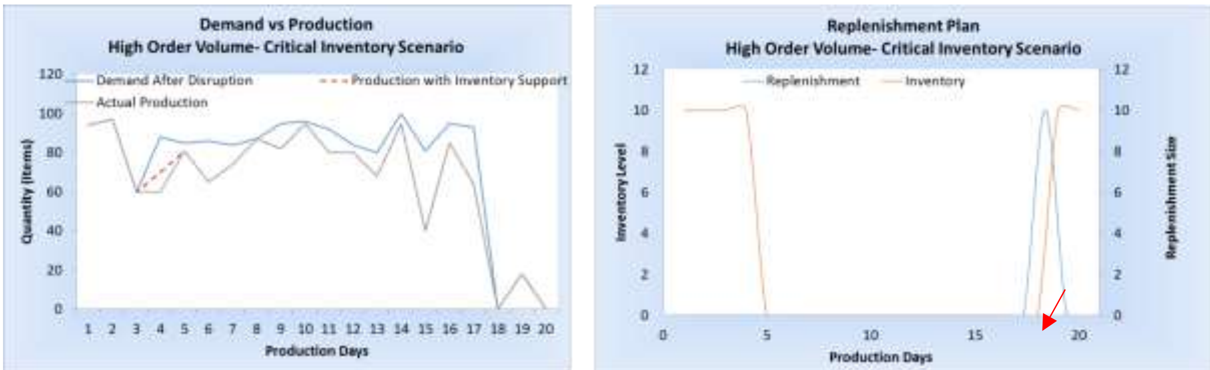


Figure 6-8: a) Second selected order demand and production for high order volume vs critical inventory level. b) Second selected order replenishment plan for high order volume vs critical inventory level.

Table 6-9: Third selected order results table high order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		95	89	87	96	84	91	100	85	80	94	87	96	100	98	95	83	80	80	92	97
Demand After Disruption		95	69	87	96	0	91	100	85	80	10	87	96	100	98	95	83	80	80	92	97
Actual Production		95	69	87	90	0	78	84	82	80	10	87	87	80	80	82	69	47	75	70	79
Production PLUS Replenishment		95	69	87	90	6	78	84	82	80	15	87	87	80	80	82	69	47	75	70	79
Borrow		0	0	0	6	0	10	0	0	0	0	0	5	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	6	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	4	10	0	0	0	0	5	5	0	0	0	0	0	0	0	0	0
Cancellation		0	20	0	0	84	0	0	0	0	84	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		95	69	87	96	0	88	84	82	80	10	87	92	80	80	82	69	47	75	70	79
Late/Unsatisfied orders		0	0	0	0	0	3	16	3	0	0	0	4	20	18	13	14	33	5	22	18

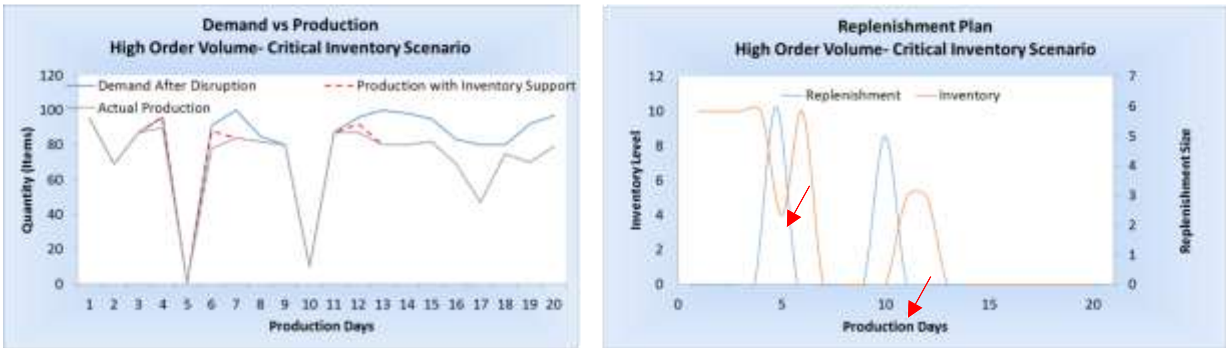


Figure 6-9: a) Third selected order demand and production for high order volume vs critical inventory level. b) Third selected order replenishment plan for high order volume vs critical inventory level.

The consequences of disruption under the high order critical inventory reveals a remarkable number of unsatisfied orders. This is due to lack of support for the production shortages. Even in the instances of replenishment of the inventory as discussed in Section 6.3.2, the wider margin of quantity between the order volumes and the inventory level implies that support is not sustainable for disruptions to be managed as expected. It is however not realistic to hold critical inventory level when higher order volumes are involved.

The variation of inventory levels with high order volumes demonstrate the impact of each with disruptions combination on the flow-shop. Based on high order volume simulation results of the three inventory levels, full inventory level demonstrates a much more sustainable selection to achieve the goal of accommodating disruptions while customer orders are being satisfied.

6.3.4 Average order vs Full inventory

In this section, the results of the experiments for the effect of disruptions with average order volume and full inventory level is presented. Table 6.10, 6.11 and 6.12 show the results of three selected order types respectively for discussion purpose.

Also, in Figure 6.10, 6.11 and 6.12 below, the graphical representation of demand production as well as the inventory level behaviour of the selected three order types are illustrated.

Table 6-10: First selected order results table average order volume vs full inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		45	50	48	42	45	41	42	47	40	49	45	50	50	46	43	46	47	41	40	44
Demand After Disruption		45	50	48	0	45	41	42	26	40	49	45	50	50	46	43	2	47	41	40	44
Actual Production		45	45	48	0	45	41	42	26	40	40	40	40	41	45	43	2	40	41	40	44
Production PLUS Replenishment		45	45	48	5	45	41	42	26	40	40	40	40	41	45	43	22	40	41	40	44
Borrow		0	5	0	0	0	0	0	0	0	9	5	10	9	1	0	0	7	0	0	0
Replenishment		0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	20	0	0	18	0
Inventory	100	100	95	95	100	100	100	100	100	100	91	86	76	67	66	66	86	79	79	97	97
Cancellation		0	0	0	42	0	0	0	21	0	0	0	0	0	0	0	44	0	0	0	0
Production with Inventory Support		45	50	48	0	45	41	42	26	40	49	45	50	50	46	43	2	47	41	40	44
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

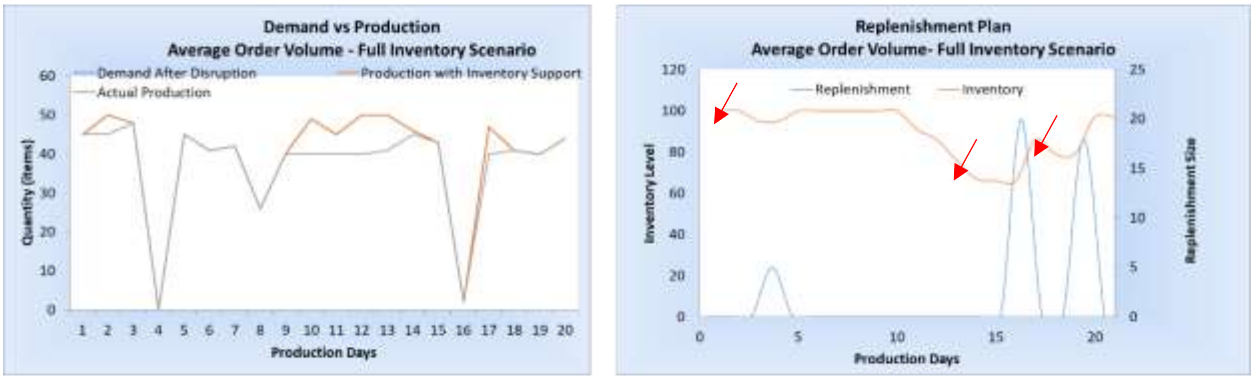


Figure 6-10: a) First selected order demand and production for average order volume vs full inventory level. b) First selected order replenishment plan for average order volume vs full inventory level.

Table 6-11: Second selected order results table average order volume vs full inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		44	47	41	48	45	46	44	47	45	46	42	44	50	40	41	45	43	40	48	42
Demand After Disruption		44	47	41	48	45	46	44	47	45	46	42	34	50	40	41	45	43	40	48	42
Actual Production		44	47	40	40	40	40	44	42	45	40	42	34	40	40	41	45	43	40	40	42
Production PLUS Replenishment		44	47	40	40	40	60	44	42	45	40	42	44	40	40	41	45	43	40	40	42
Borrow		0	0	1	8	5	6	0	5	0	6	0	0	10	0	0	0	0	0	8	0
Replenishment		0	0	0	0	0	20	0	0	0	0	0	10	0	0	0	0	0	0	0	0
Inventory	100	100	100	99	91	86	100	100	95	95	89	89	99	89	89	89	89	89	89	81	81
Cancellation		0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0
Production with Inventory Support		44	47	41	48	45	46	44	47	45	46	42	34	50	40	41	45	43	40	48	42
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

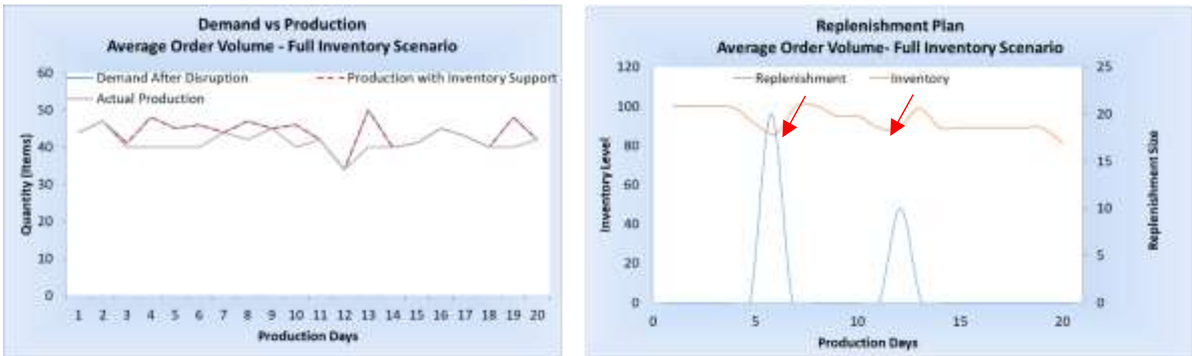


Figure 6-11: a) Second selected order demand and production for average order volume vs full inventory level. b) Second selected order replenishment plan for average order volume vs full inventory level.

Table 6-12: Third selected order results table average order volume vs full inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		45	49	47	46	44	41	50	45	41	44	47	46	40	48	44	43	50	50	42	47
Demand After Disruption		45	49	47	46	0	0	50	45	41	44	32	46	40	48	44	43	50	50	32	47
Actual Production		45	46	47	46	0	0	50	45	41	44	32	46	40	48	44	43	40	40	32	47
Production PLUS Replenishment		45	46	47	46	3	0	50	45	41	44	32	46	40	48	44	43	40	40	50	47
Borrow		0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0
Replenishment		0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	100	100	97	97	97	100	100	100	100	100	100	100	100	100	100	100	100	90	80	80	80
Cancellation		0	0	0	0	44	41	0	0	0	0	15	0	0	0	0	0	0	0	10	0
Production with Inventory Support		45	49	47	46	0	0	50	45	41	44	32	46	40	48	44	43	50	50	32	47
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

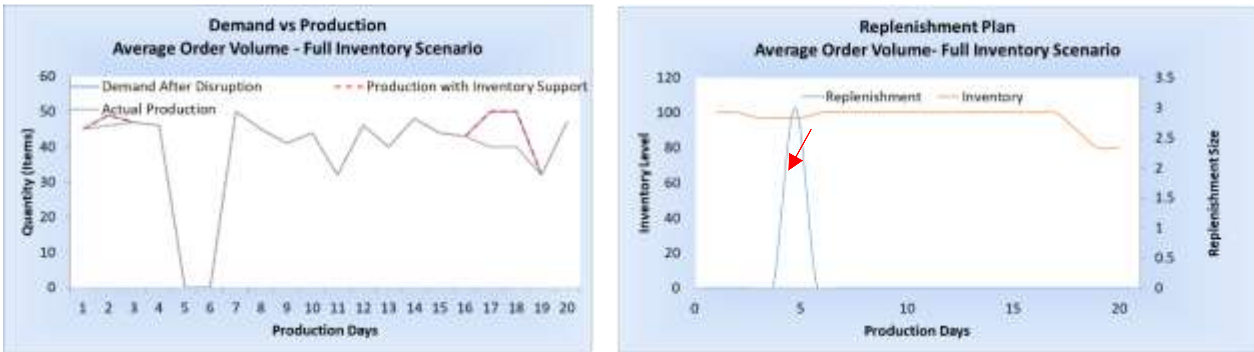


Figure 6-12: a) Third selected order demand and production for average order volume vs full inventory level. b) Third selected order replenishment plan for average order volume vs full inventory level.

The three order examples (Tables 6.10, 6.11 and 6.12), show a more adaptive production process despite disruptions. This is evident as there was not unsatisfied order recorded over the entire production period. In this scenario example, the flow-shop production conditions such as machine and operator utilisation appear efficient as over 15 days of the period of production show actual production equal to demand after disruption. For this reason, inventory support was only required on few occasions. It can be established that, in terms of number of orders completed against late or unsatisfied order, average order volumes with high inventory level demonstrate a promising combination. However, the inventory levels were shown at the maximum level for most of the production period. This implies holding unnecessary high inventory levels. Thus, the production support, the intention of keeping inventory is not fully justified. Especially when disruptions have not caused a reduction in the number of actual order production.

In all the three instances, the disruptions on the production flow-shop appear to be sufficiently managed with excessively inventory levels. For the most period of production, the three factors on demand production side remain align. This indicate that even though there are disruptions, the impact does not affect normal production plan which could cause unsatisfied customer orders. The inventory of the three orders were kept relatively high since very few numbers of inventory borrow were made. Although the impacts of disruptions were managed in this scenario example, inventory support have not been optimally utilised. This suggest less reliance of inventory support when production resources are effectively utilised to meet demand. This is the case in this scenario.

6.3.5 Average order vs Safe inventory

In this section, the average order volume is tested with safe inventory level. The results of the three selected order types are presented in Table 6.6 below.

Table 6-13: First selected order results table average order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		44	40	41	47	46	43	46	50	45	49	44	40	47	43	45	42	41	40	47	48
Demand After Disruption		44	40	41	47	46	43	46	50	45	49	44	40	47	43	45	30	41	40	19	48
Actual Production		44	40	41	40	41	41	40	40	44	40	40	40	40	40	41	30	41	40	19	42
Production PLUS Replenishment		44	40	41	40	41	41	40	40	44	40	40	40	40	40	41	40	41	40	16	42
Borrow		0	0	0	7	5	2	6	10	1	9	4	0	6	0	0	0	0	0	0	6
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0
Inventory	50	50	50	50	43	38	36	30	20	19	10	6	6	0	0	0	10	10	10	10	4
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	28	0
Production with Inventory Support		44	40	41	47	46	43	46	50	45	49	44	40	46	40	41	30	41	40	19	48
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	1	3	4	0	0	0	0	0

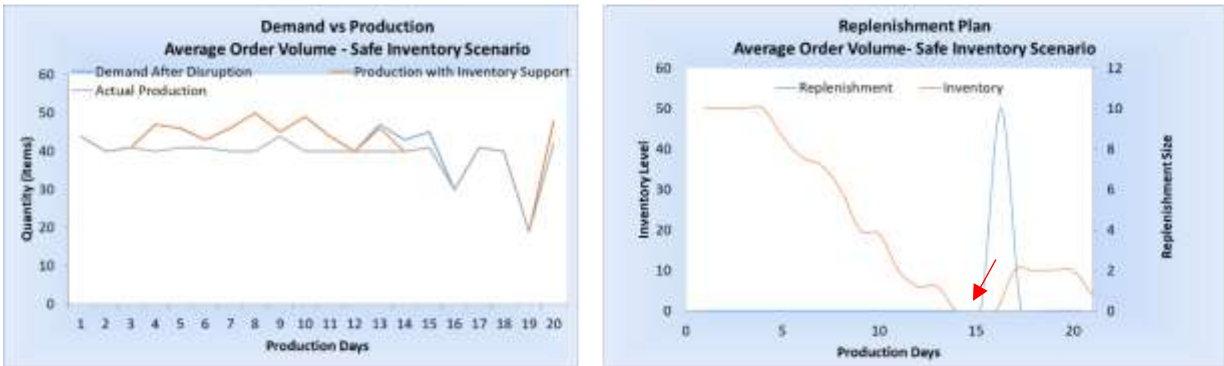


Figure 6-13: a) First selected order demand and production for average order volume vs safe inventory level. b) First selected order replenishment plan for average order volume vs safe inventory level.

Table 6-14: Second selected order results table average order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		42	48	40	43	41	50	40	42	48	40	50	43	49	49	41	40	46	43	44	43
Demand After Disruption		42	48	40	43	41	50	40	42	48	40	50	43	49	49	41	40	46	43	44	43
Actual Production		42	40	40	40	41	40	40	42	40	40	42	43	40	40	41	40	40	40	44	43
Production PLUS Replenishment		42	40	40	40	41	40	40	42	40	40	42	43	40	40	41	40	40	40	69	43
Borrow		0	8	0	3	0	10	0	0	8	0	8	0	9	4	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0
Inventory	50	50	42	42	39	39	29	29	29	21	21	13	13	4	0	0	0	0	0	21	21
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		42	48	40	43	41	50	40	42	48	40	50	43	49	44	41	40	40	40	44	43
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	6	3	0	0

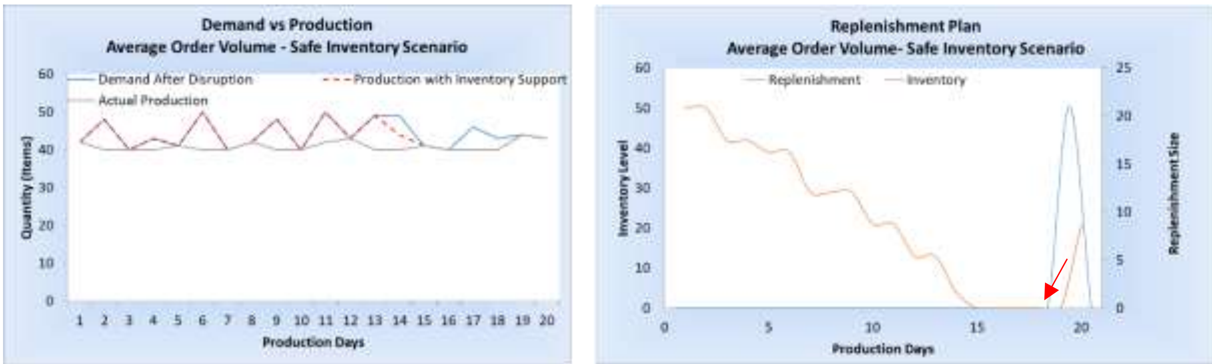


Figure 6-14: a) Second selected order demand and production for average order volume vs safe inventory level. b) Second selected order replenishment plan for average order volume vs safe inventory level.

Table 6-15: Third selected order results table average order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		47	46	45	41	47	40	40	48	41	44	50	47	42	50	46	41	44	47	48	45
Demand After Disruption		47	46	45	41	47	0	40	48	41	44	50	47	42	50	46	41	44	37	48	45
Actual Production		45	0	40	41	41	0	40	45	41	40	45	40	42	45	46	41	40	37	40	40
Production PLUS Replenishment		45	0	40	41	41	29	40	45	41	40	45	40	42	45	46	41	40	47	40	40
Borrow		2	46	2	0	0	0	0	3	0	4	5	7	0	5	0	0	4	0	8	3
Replenishment		0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	10	0	0
Inventory	50	48	2	0	0	0	29	29	26	26	22	17	10	10	5	5	5	1	11	3	0
Cancellation		0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	10	0	0
Production with Inventory Support		47	46	42	41	41	0	40	48	41	44	50	47	42	50	46	41	44	37	48	43
Late/Unsatisfied orders		0	0	3	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

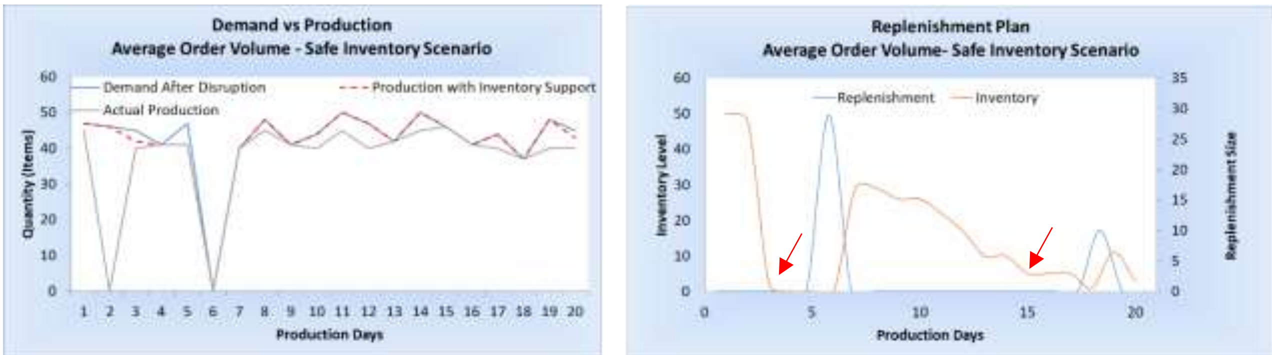


Figure 6-15: a) Third selected order demand and production for average order volume vs safe inventory level. b) Third selected order replenishment plan for average order volume vs safe inventory level.

Unlike the full inventory scenario above, there are unsatisfied order recorded in this scenario as the consequence of disruptions. This is because there is limited opportunity for replenishment of inventory. However, it can be observed the effect of flow-shop resources improves production processes as demand after disruption is equal to the actual production in most days of the production period. Interestingly in cases where inventory levels were at zero in days 15 and 16 of Table 6.14, reveal no unsatisfied order.

The drastic drop in the levels of inventory of the three orders means that without effective resources utilisation and optimal scheduling provided by the heuristic the consequence would have been higher number of unsatisfied orders. In a long run, if the resources utilisation drops, the system might experience increase in the number of unsatisfied orders especially when inventory replenishment remains limited.

6.3.6 Average order vs Critical inventory

This section presents the experimental results based on average order volumes and critical inventory level. In Table 6.16, 6.17 and 6.18 the production activities of selected three orders are shown.

Table 6-16: First selected order results table average order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		43	41	42	46	47	42	45	49	44	48	43	41	47	42	44	43	42	41	40	49
Demand After Disruption		43	41	42	0	47	42	45	49	44	48	43	41	47	42	44	43	42	41	40	49
Actual Production		43	41	42	0	40	42	40	40	44	40	40	40	40	42	41	40	42	40	40	42
Production PLUS Replenishment		43	41	42	0	40	42	40	40	44	40	40	40	40	42	41	40	42	40	40	42
Borrow		0	0	0	0	7	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cancellation		0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		43	41	42	0	47	42	43	40	44	40	40	40	40	42	41	40	42	40	40	42
Late/Unsatisfied orders		0	0	0	0	0	0	2	9	0	8	3	1	7	0	3	3	0	1	0	7

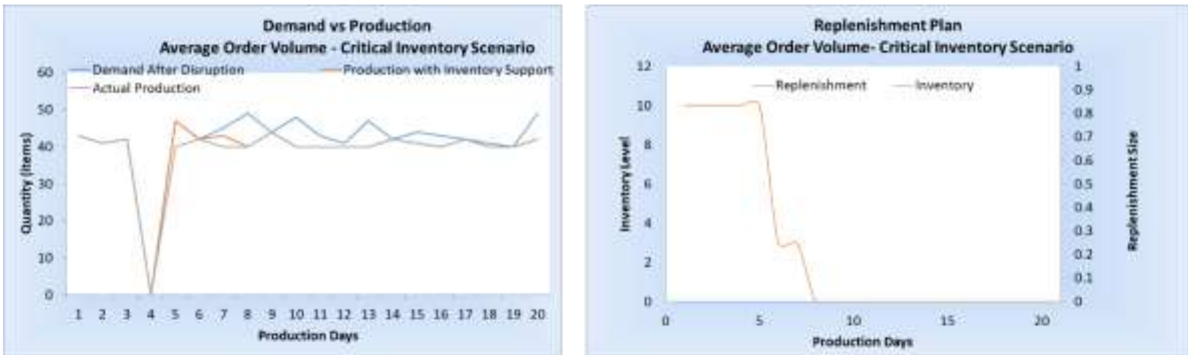


Figure 6-16: a) First selected order demand and production for average order volume vs critical inventory level. b) First selected order replenishment plan for average order volume vs critical inventory level.

Table 6-17: Second selected order results table average order volume vs critical inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		44	50	42	45	43	47	43	45	41	50	48	45	47	42	43	44	48	45	46	47
Demand After Disruption		44	50	42	45	43	47	43	45	5	50	48	0	47	42	43	44	48	29	46	47
Actual Production		40	40	42	40	41	40	40	40	5	40	42	0	40	42	43	40	40	29	40	43
Production PLUS Replenishment		40	40	42	40	41	40	40	40	10	40	42	6	40	42	43	40	40	34	40	43
Borrow		4	6	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0
Replenishment		0	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0	0
Inventory	10	6	0	0	0	0	0	0	0	5	0	0	6	0	0	0	0	0	5	0	0
Cancellation		0	0	0	0	0	0	0	0	36	0	0	45	0	0	0	0	0	16	0	0
Production with Inventory Support		44	46	42	40	41	40	40	40	5	45	42	0	46	42	43	40	40	29	45	43
Late/Unsatisfied orders		0	4	0	5	2	7	3	5	0	5	6	0	1	0	0	4	8	0	1	4

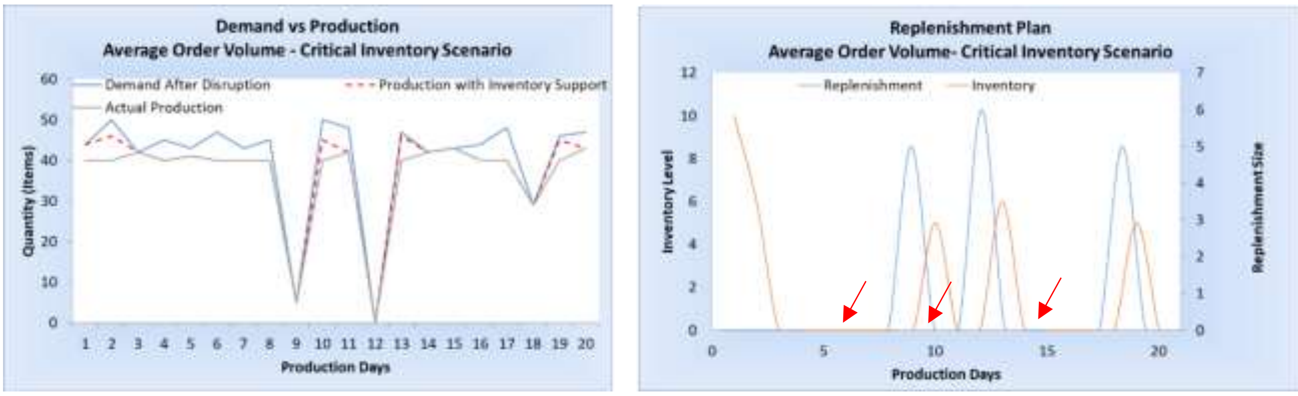


Figure 6-17: a) Second selected order demand and production for average order volume vs critical inventory level. b) Second selected order replenishment plan for average order volume vs critical inventory level.

Table 6-18: Third selected order results table average order volume vs critical inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		45	44	42	48	45	50	47	46	43	49	45	50	44	41	40	40	49	41	49	48
Demand After Disruption		45	44	42	48	45	50	47	46	43	49	45	50	44	41	40	40	49	41	49	48
Actual Production		45	44	42	48	40	40	40	46	43	40	45	40	42	41	40	40	40	41	40	40
Production PLUS Replenishment		45	44	42	48	40	40	40	46	43	40	45	40	42	41	40	40	40	46	40	40
Borrow		0	0	0	0	5	5	0	0	0	0	0	0	0	0	0	0	0	0	5	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0
Inventory	10	10	10	10	10	5	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		45	44	42	48	45	45	40	46	43	40	45	40	42	41	40	40	40	41	40	40
Late/Unsatisfied orders		0	0	0	0	0	5	7	0	0	9	0	10	2	0	0	0	9	0	4	8

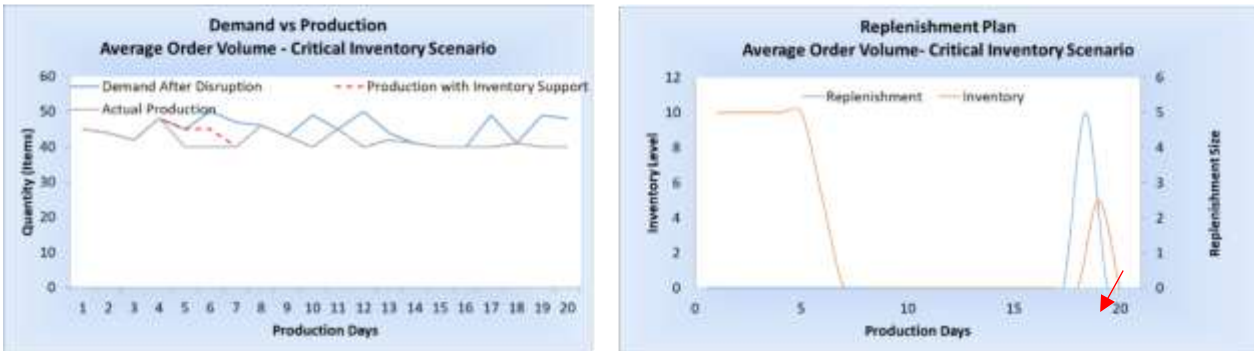


Figure 6-18: a) Third selected order demand and production for average order volume vs critical inventory level. b) Third selected order replenishment plan for average order volume vs critical inventory level.

The effect of disruptions on the three order examples show many instances of late or unsatisfied customer orders. This is because inventory limit was not sufficient to support production shortages caused by disruptions. The critical levels of inventory here mean that inventories are exhausted quickly. It appears more damaging when there are fewer replenishment opportunities. In Table 6.17, where inventory replenishment occurred on 3 occasions, they were not enough to accommodate disruptions. Over 10 days of the production period, the actual production is less than the demand after disruptions. Apart from the critical inventory condition, the inability of the production flow-shop to match production of demand after disruption can be further understood from the resource utilisation point of view.

Order inventory in Figure 6.18b tend toward zero level within first half of the production period. This is because the orders experienced more and quicker borrow due to disruption causing more unsatisfied customer orders. The impact of the disruption is felt with high number of unsatisfied orders during the constant zero level of inventory. This continues for a longer period as there were no instances of inventory replenishment, especially in Table 6.16 which reflects in the graphs of Figure 6.16. When there are replenishments, as the case in Figure 6.17 and one instance (day 18) in Figure 6.18, they were not enough to support the declining production levels.

In Table 6.17, the number of days in which order are left unsatisfied many compared to Table 6.16 and Table 6.18. This is because inventory support was used up on the second day of production, while inventory level declined gradually until day 6 in Table 6.16 and day 5 in Table 6.18. The situation of very limited or lack of replenishment attempt (as the case of Table 6.16 and Figure 6.16) in the three experiments can be linked with the limited or no order cancellation disruption. This is because, order cancellation disruption creates available time that can be considered for replenishment along with machines and operators availability. However, because the combined disruptions occurrence is set at random, it means different disruption behaviour can cause different production reactions. Regardless, keeping critical level of inventory to deal with average volume of orders, as it is the case in these experiments, is most likely unsuitable for improved production performances.

6.3.7 Low order vs Full inventory

In this section, the results of the experiment are presented for low order volumes with full inventory levels. Table 6.19, 6.20, and 6.21 shows results of three selected orders during the 20 days production period.

Table 6-19: First selected order results table low order volume vs full inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		22	25	20	20	21	25	24	24	22	20	21	23	25	22	22	20	25	21	22	20
Demand After Disruption		0	0	20	20	21	25	24	24	22	20	21	23	25	22	22	20	25	21	22	20
Actual Production		0	0	20	20	21	25	24	24	22	20	21	23	25	22	22	20	25	21	22	20
Production PLUS Replenishment		0	0	20	20	21	25	24	24	22	20	21	23	25	22	22	20	25	21	22	20
Borrow		0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Cancellation		22	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		0	0	20	20	21	25	24	24	22	20	21	23	25	22	22	20	25	21	22	20
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

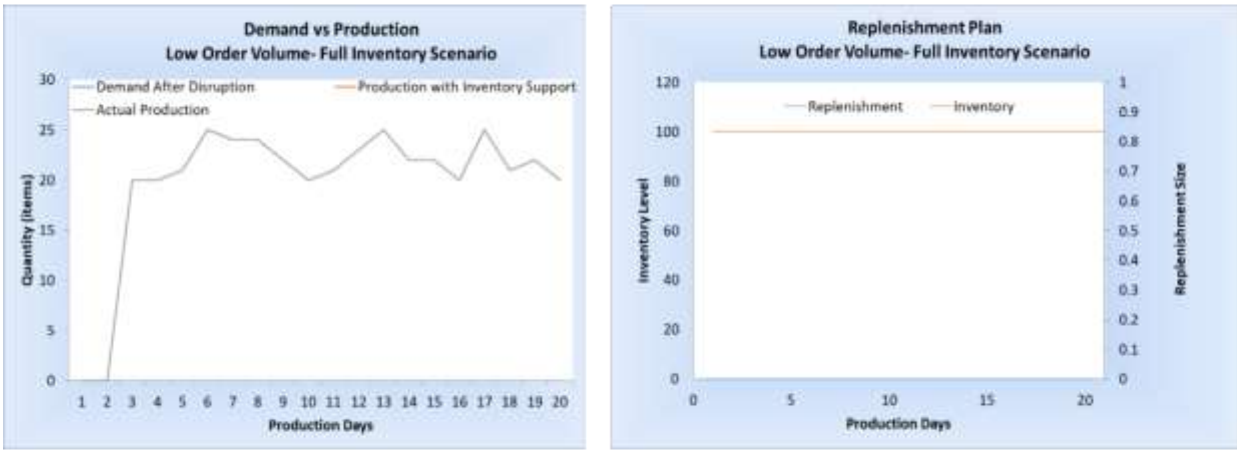


Figure 6-19: a) First selected order demand and production for low order volume vs full inventory level. b) First selected order replenishment plan for low order volume vs full inventory level

Table 6-20: Second selected order results table low order volume vs full inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		25	22	21	25	24	22	20	21	25	24	22	25	21	22	21	22	20	21	25	23
Demand After Disruption		25	22	21	25	24	22	20	11	25	24	22	23	21	22	5	22	20	21	25	23
Actual Production		25	22	21	25	24	22	20	11	20	24	22	23	21	22	5	22	20	21	25	23
Production PLUS Replenishment		25	22	21	25	24	22	20	11	20	24	22	23	21	22	10	22	20	21	25	23
Borrow		0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0
Inventory	100	100	100	100	100	100	100	100	100	95	95	95	95	95	95	100	100	100	100	100	100
Cancellation		0	0	0	0	0	0	0	10	0	0	0	2	0	0	16	0	0	0	0	0
Production with Inventory Support		25	22	21	25	24	22	22	11	25	24	22	23	21	22	5	22	20	21	25	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

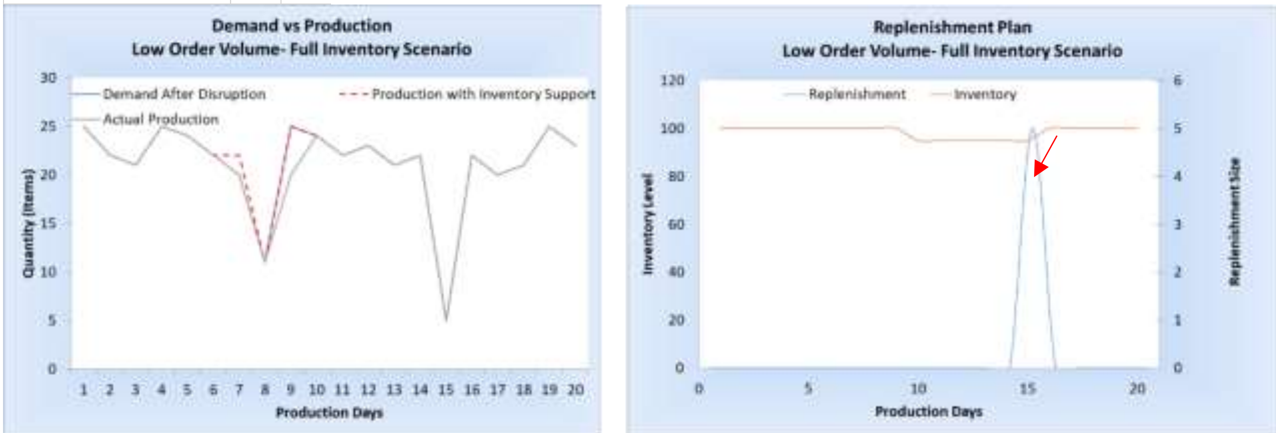


Figure 6-20: a) Second selected order demand and production for low order volume vs full inventory level. b) Second selected order replenishment plan for low order volume vs full inventory level.

Table 6-21: Third selected order results table low order volume vs full inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		22	25	20	20	21	25	23	23	24	22	20	21	20	21	22	24	21	22	20	23
Demand After Disruption		22	25	0	20	21	25	23	23	24	22	20	21	20	21	22	0	21	22	20	23
Actual Production		22	25	0	20	21	25	23	23	24	22	20	21	20	21	22	0	21	22	20	23
Production PLUS Replenishment		22	25	0	20	21	25	23	23	24	22	20	21	20	21	22	0	21	22	20	23
Borrow		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Cancellation		0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0
Production with Inventory Support		22	25	0	20	21	25	23	23	24	22	20	21	20	21	22	0	21	22	20	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

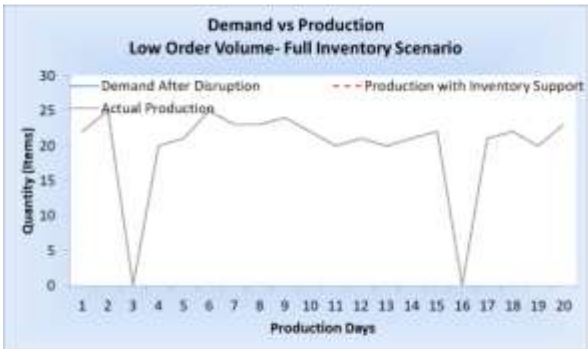


Figure 6-21: a) Third selected order demand and production for low order volume vs full inventory level. b) Third selected order replenishment plan for low order volume vs full inventory level.

In all the selected three orders, there were no significant effect of disruptions in terms of number of actual productions, and unsatisfied orders. All orders were completed with no shortages or inventory borrow on each days of the production period. Although on day 9 of Table 6.20, there was a reduced in inventory by 5 units of order. The impact was not entirely experienced on the production flow-shop.

The completely parallel level of inventories at the maximum demonstrates why inventory support is suitable for low order volumes even as disruptions occur. However, at high level, the inventory appears stagnant with no justifiable need to associate inventory support when the demand volumes are low.

6.3.8 Low order vs Safe inventory

In this section, the results of low order and safe inventory level are presented. Table 6.22, 6.23, and 6.24 and figure 6.22, 6.23, and 6.24 show behaviour of the three selected orders to impact of disruption in this situation.

Table 6-22: First selected order results table low order volume vs safe inventory level.

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		21	22	20	25	24	25	25	20	20	25	24	23	22	20	20	25	23	21	20	24
Demand After Disruption		21	22	20	25	24	25	25	20	20	25	24	23	22	20	20	25	21	21	5	24
Actual Production		21	22	20	20	21	20	25	20	20	21	24	23	22	20	20	25	21	21	5	24
Production PLUS Replenishment		21	22	20	20	21	20	25	20	20	21	24	23	22	20	20	25	35	21	5	24
Borrow		0	0	0	5	3	5	0	0	0	4	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0
Inventory	50	50	50	50	45	42	37	37	37	37	33	33	33	33	33	33	33	47	47	47	47
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	15	0
Production with Inventory Support		21	22	22	25	24	25	25	20	20	25	24	23	22	20	20	20	21	21	5	24
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

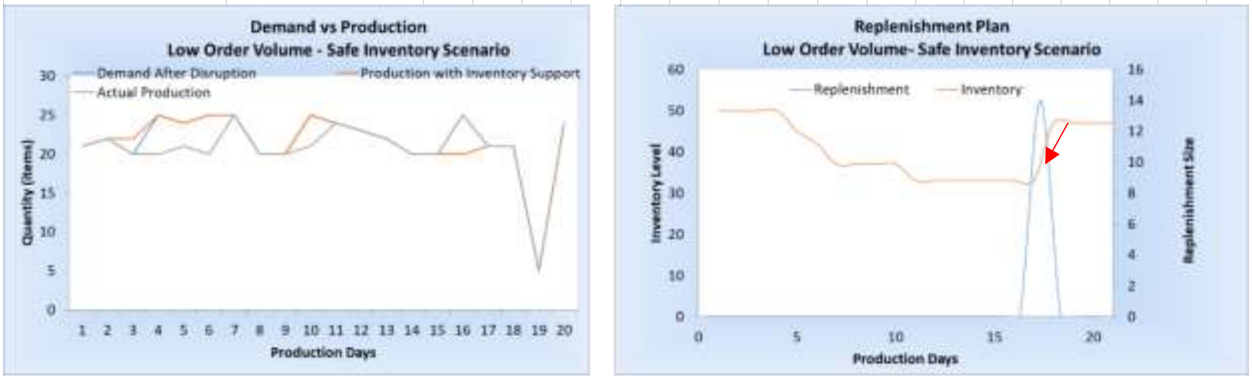


Figure 6-22: a) First selected order demand and production for low order volume vs safe inventory level. b) First selected order replenishment plan for low order volume vs safe inventory level

Table 6-23: Second selected order results table low order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		22	20	21	25	23	21	23	24	21	25	25	23	22	21	20	20	24	25	23	22
Demand After Disruption		22	20	21	25	23	21	23	24	21	25	25	23	22	21	20	20	24	25	23	22
Actual Production		22	20	21	20	23	21	23	24	21	20	20	23	22	21	20	20	24	25	23	22
Production PLUS Replenishment		22	20	21	20	23	21	23	24	21	20	20	23	22	21	20	20	24	25	23	22
Borrow		0	0	0	5	0	0	0	0	0	5	5	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	50	50	50	50	45	45	45	45	45	45	40	35	35	35	35	35	35	35	35	35	35
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		22	20	21	25	23	21	23	23	21	25	25	23	22	21	20	20	24	25	23	22
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

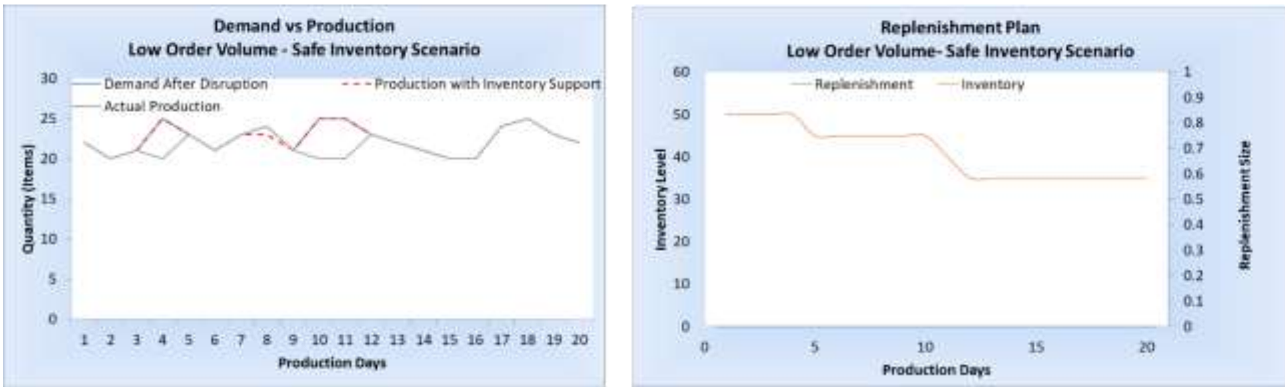


Figure 6-23: a) Second selected order demand and production for low order volume vs safe inventory level. b) Second selected order replenishment plan for low order volume vs safe inventory level.

Table 6-24: Third selected order results table low order volume vs safe inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		24	25	21	20	20	22	22	25	23	21	24	22	24	23	21	20	24	25	20	21
Demand After Disruption		24	25	21	20	20	22	22	25	23	21	0	0	24	23	21	20	24	25	20	21
Actual Production		24	0	21	20	20	22	22	20	23	21	0	0	24	23	21	20	24	20	20	21
Production PLUS Replenishment		24	0	21	20	20	22	22	20	23	21	13	2	24	23	21	20	24	20	23	21
Borrow		0	25	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	5	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	13	2	0	0	0	0	0	0	3	0
Inventory	50	50	25	25	25	25	25	25	20	20	20	33	35	35	35	35	35	35	30	33	33
Cancellation		0	0	0	0	0	0	0	0	0	0	24	22	0	0	0	0	0	0	0	0
Production with Inventory Support		24	25	21	20	20	22	22	25	23	21	0	0	24	23	23	20	24	25	20	21
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 6-24: a) Third selected order demand and production for low order volume vs safe inventory level. b) Third selected order replenishment plan for low order volume vs safe inventory level

Like the result of low order volumes when inventory is high, this scenario record no unsatisfied orders. This is because production with inventory supports are equal to demand after disruption during the production period.

6.3.9 Low order vs Critical inventory

In this section, the results of the experiment conducted for low order volumes and critical inventory for three selected orders are discussed as shown in Table 6.25, 6.26, and 6.27 and Figure 6.25, 6.26 and 6.27 below.

Table 6-25: First selected order results table low order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		21	22	21	20	24	20	22	25	20	25	23	22	24	24	20	25	20	22	24	23
Demand After Disruption		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Actual Production		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Production PLUS Replenishment		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Borrow		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Cancellation		0	0	0	20	0	0	22	0	0	25	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		21	22	21	0	24	20	0	25	20	0	23	22	24	24	20	25	20	22	24	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

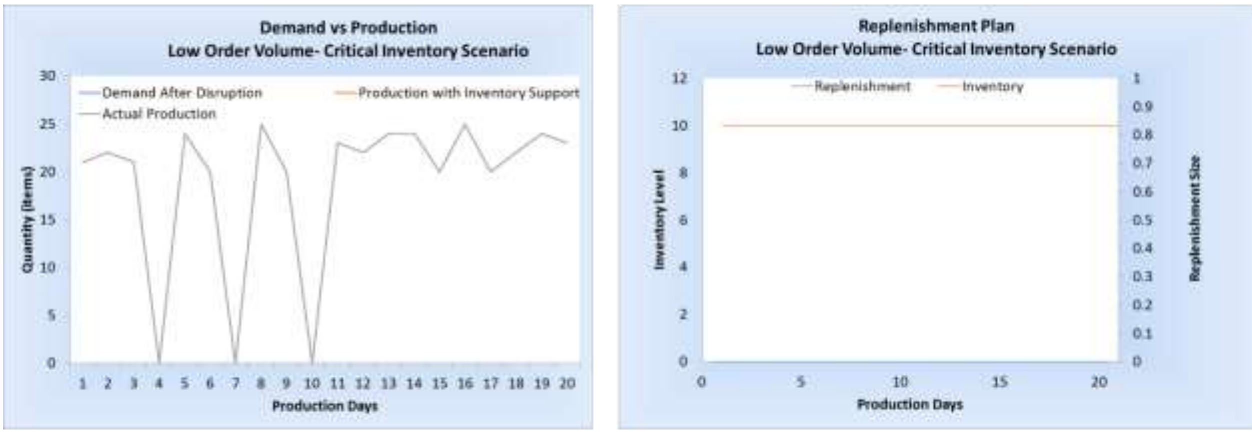


Figure 6-25: a) First selected order demand and production for low order volume vs critical inventory level. b) First selected order replenishment plan for low order volume vs critical inventory level.

Table 6-26: Second selected order results table low order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	25	23	21	20
Demand After Disruption		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	25	23	21	20
Actual Production		24	18	16	21	20	20	21	23	22	21	20	21	23	20	20	18	20	20	21	20
Production PLUS Replenishment		24	18	16	27	20	20	29	23	22	21	20	21	23	20	20	18	20	20	21	20
Borrow		0	2	4	0	3	5	0	0	0	0	4	0	0	0	3	3	0	0	0	0
Replenishment		0	0	0	6	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	8	4	10	7	2	10	10	10	10	6	6	6	6	3	0	0	0	0	0
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		24	20	20	21	23	25	21	23	22	21	24	21	23	20	23	21	20	20	21	20
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	3	0	0

Figure 6-26: a) Second selected order demand and production for low order volume vs critical inventory level. b) Second selected order replenishment plan for low order volume vs critical inventory level

Table 6-27: Third selected order results table low order volume vs critical inventory level

		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	Day 11	Day 12	Day 13	Day 14	Day 15	Day 16	Day 17	Day 18	Day 19	Day 20
Demand		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Demand After Disruption		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Actual Production		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Production PLUS Replenishment		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Borrow		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Replenishment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Cancellation		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Production with Inventory Support		24	21	20	25	21	24	20	20	24	21	22	22	20	21	21	25	25	20	20	23
Late/Unsatisfied orders		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

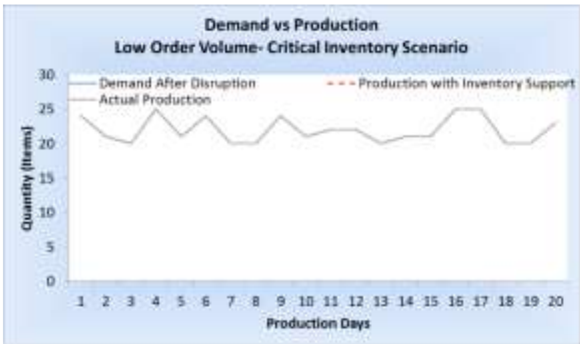


Figure 6-27: a) Third selected order demand and production for low order volume vs critical inventory level. b) Third selected order replenishment plan for low order volume vs critical inventory level.

Even at critical level of inventory, production appears not affected by disruptions. In 6.25 and 26, the inventory level remains unchanged throughout the entire production period.

In every instances of the low order volumes, the impact of disruptions has no threat on production levels and hence inventories were kept at considerable high level. For all scenarios, it can be established that the effects of disruptions can be managed when inventory support is sufficient. However, flow-shop resources utilisation factor is equally significant to disruption adaptation. In section 6.4, the production key performance indicators (KPIs) is discussed to understand machine-operation relationship within the system and their impact on productions.

6.4 Production Key Performance Indicators (KPIs)

In manufacturing facilities, problems are usually tracked by some key factors of improvements. Key Performance Indicators (KPIs) are regarded as factors that are significant in the assessment and measurement of production processes. To determine the impact; success or the shortfall of the proposed approach for flow-shop production processes, the follow KPIs are considered;

1. Operators' total time on machines
2. Resource Utilisation
3. Total number of late/unsatisfied orders

The proposed approach is designed to utilise the 'available free time slot' created by disruptions to replenish borrowed order from inventory support. However, even though the free time slot might be available, it also depends on both machines and operators' availability to be utilised. Likewise, the utilisation of the free time slot depends on the number of order item that can fit in based on order process time.

6.4.1 KPI 1: Operators' Total Time on Machines

The total time spend by operator on machines for assigned job is relative to the flow-shop productivity. When the total idle time is greater, the total busy time is reduced and hence lower productivity level. As operators engage with machines to make busy on order production, the total time spend by operator is significant to measure the performance of the system. Figure 6.28 depicts the graphical representation of operators' total busy time on machines under high order and full, safe and critical inventory scenarios. The results compare operators' time for both "As-Is" and proposed heuristic for the 27 operators on the three shifts production periods.

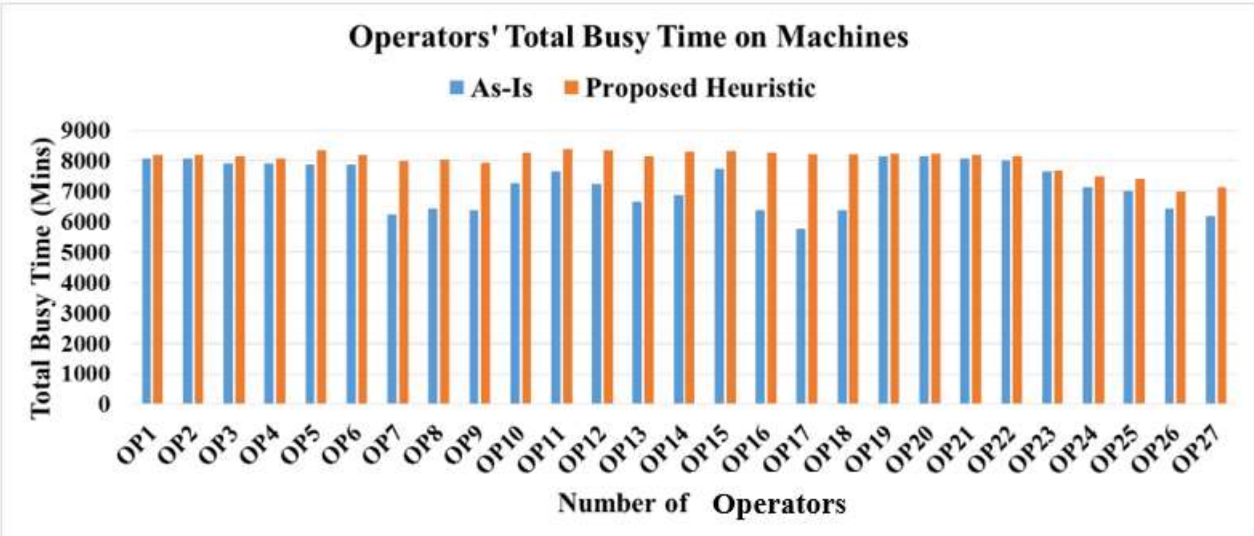


Figure 6-28 a) **Total Busy Time for High Order Full Inventory Scenario**.

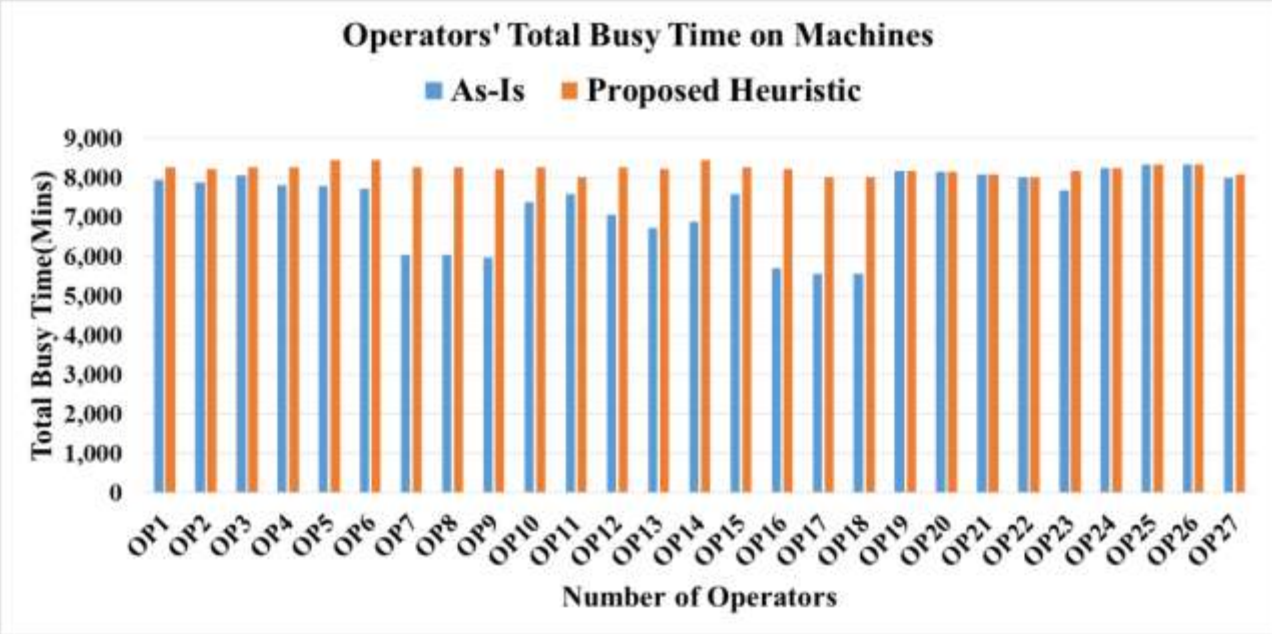


Figure 6-29. b) **Total Busy Time for High Order Safe Inventory Scenario.**

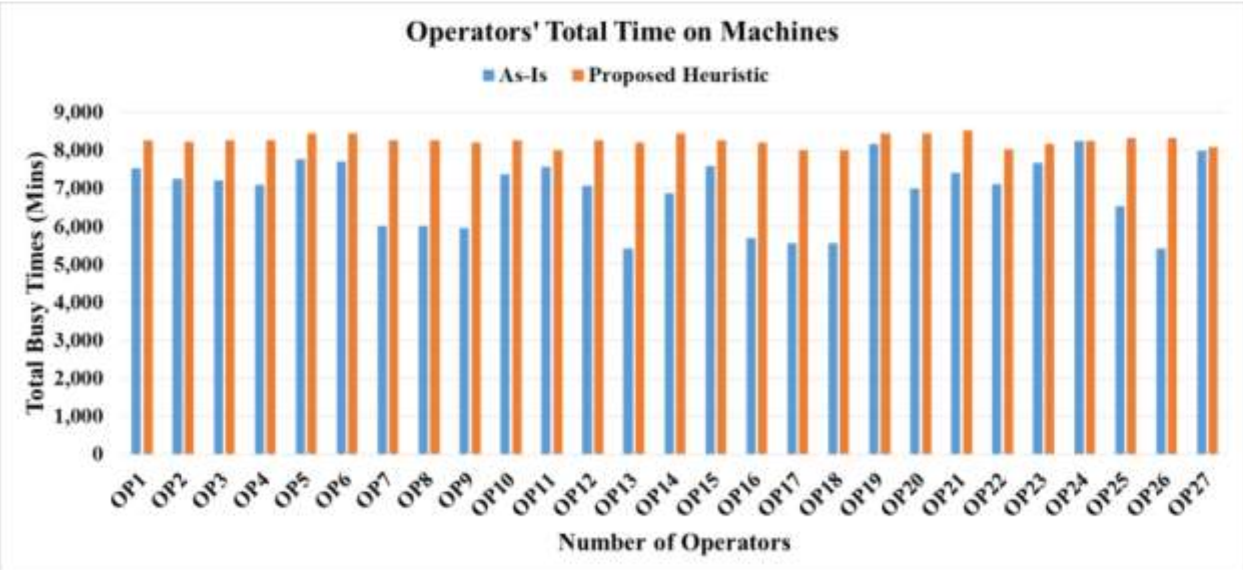


Figure 6-30 c) **Total Busy Time for High Order Critical Inventory Scenario**.

Each of the three shifts have 9 operators, which means operators 1 to 9 worked in shift 1, operators 10 to 18 worked in shift 2 while operators 19 to 27 worked in shift 3 respectively (Table 1 of Appendix). The activities of each of the operator in each shift depends on individual availability, skills, machines availability and the nature of disruptions occurrences. The graphs (Figure 6.28, Figure 6.29 and Figure 6.30) showing operators activities is presented as a block of 3 shifts (27 operators), 2 shifts (18 operators), and 1 shift (9 operators) respectively. This is also the case in (Figure 6.31, Figure 6.32 and Figure 6.33).

In Figure 6.28a of the full inventory scenario, the total time spent by the first five operators seems to be closely equal for the two cases (As-Is and proposed heuristic). This is because disruptions have no major effect on operators' performance at the early stage since inventory is available to support production shortages. However, the time spent by operator number 7, 8, 9 and 10 drops compared to the proposed heuristic case. This is due to addition scheduled replenishment orders creating more queues. The first set of machines got fully engaged and are experiencing bottleneck, leaving the operators idle as they wait longer for the next job. On the second shift, the total spent by operators 16, 17 and 18 also drop while spending more time under the proposed heuristic case. The drop in the time spent on machines consequently increase total idle time for both operators and machines. In some cases, the drop in the time on machine could be because of lack of skilled operator skill assigned to function on specific machines processes. The skills of operators are considered in the system where operators can be selected to possess specific machine skills and other do not. Most importantly, the increase in the total time spent on machines by operators for the proposed heuristic is due optimal scheduling rule implemented. Like figure 6.28a, figure 6.28b and 6.28c reveal drop in the total busy of operators on machine in a relatively similar pattern. And increase in the proposed heuristic, suggesting lesser idle time for both machine and operators in the three scenarios.

In Figure 6.29, the operator total busy time on machines for average order and full, safe and critical inventory is presented. The result reveals the time for each of 18 operators involve in the two shifts period over 20 days.

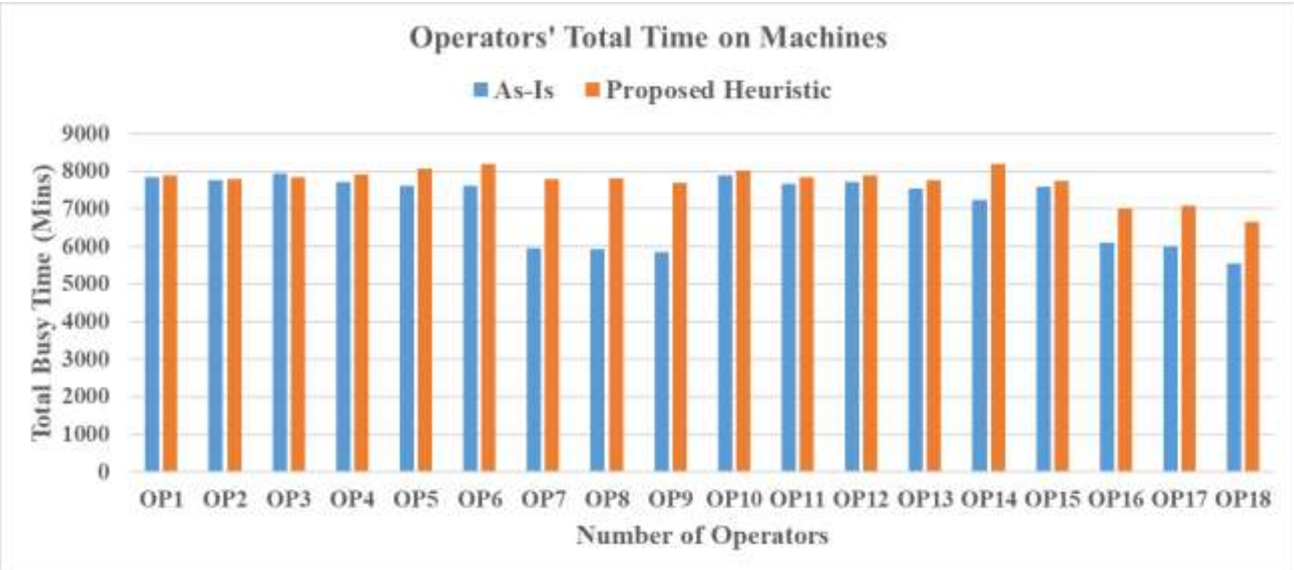


Figure 6-31: a) **Total Busy Time for Average Order Full Inventory Scenario.**

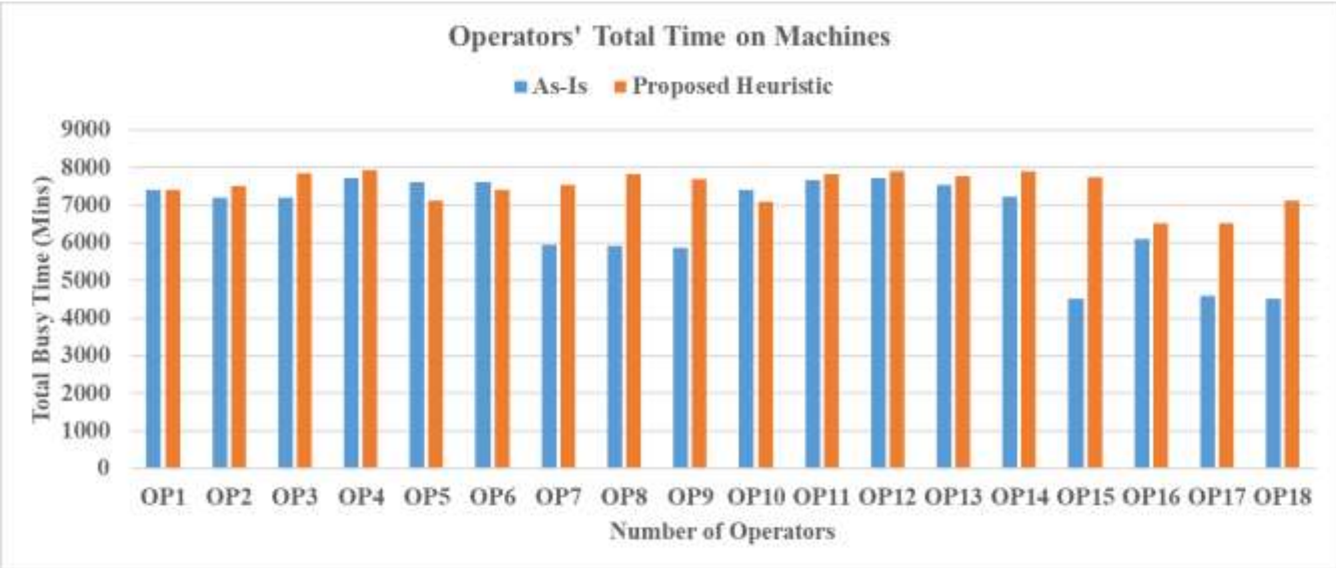


Figure 6-32: b) Total Busy Time for Average Order Safe Inventory Scenario.

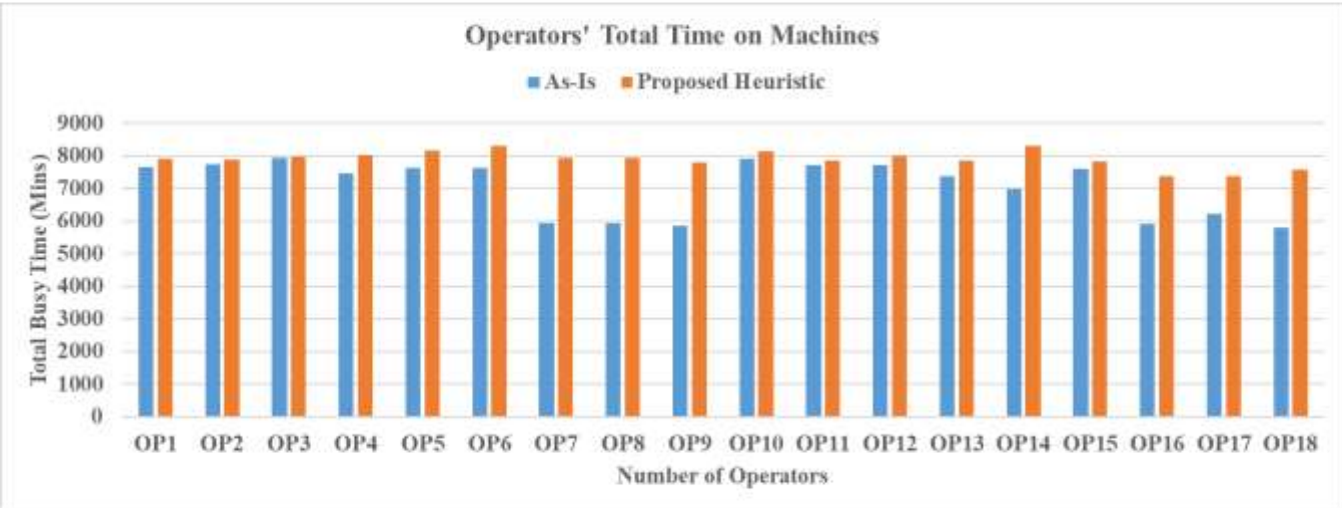


Figure 6-33: c) Total Busy Time for Average Order Critical Inventory Scenario.

Comparing the total time machine for all three scenarios is relatively similar with little changes in the two cases. However, the consistent drop in the time of operators 7, 8 and 9 indicates these operators have no skills to function on some machine operation. And, for each operator busy time, the proposed heuristic shows an improvement. This means the proposed heuristic successfully re-scheduled idle operators to available machine to minimise number of queues and idle time. In both cases, the total busy time difference is significant improvement in terms of heuristic implementation and justifies the higher production performance compared to "As-Is" case.

In Figure 6.30 below, the result of ‘As-Is’ and the proposed heuristic cases of operators’ total time on machines is shown. This is related to 9 operators on a single shift for low order under full, safe and critical inventory level scenarios.

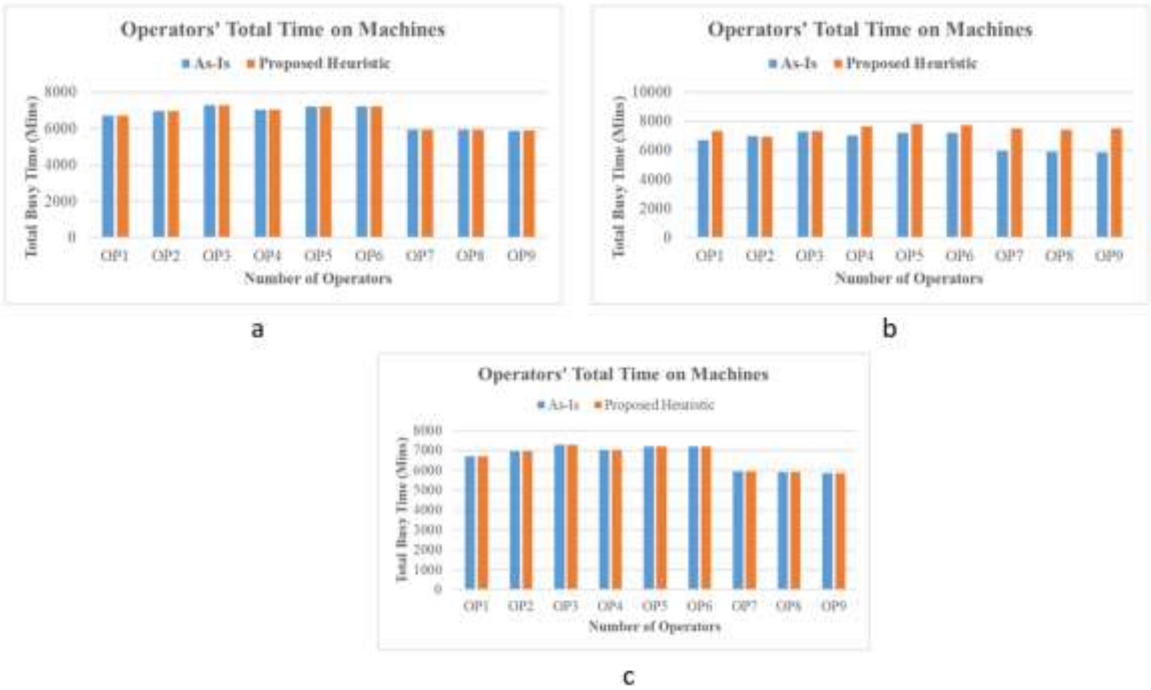


Figure 6-34: a) **Total Busy Time for Low Order Full Inventory Scenario. b) Total Busy Time for Low Order Safe Inventory Scenario. c) Total Busy Time for Low Order Critical Inventory Scenario.**

In Figure 6.30a and 6.30c, it appears there are no difference in the amount of time spent by all operators. This indicates that even when there are disruptions, there was no major operators’ allocation stress on machines. As a result, there is no improvement over the “As-Is” scenario when the inventory is either high or critical under low order volumes. Although, in figure 6.30b there is slight improvement with more time spent by the 9 operators under the proposed heuristic compared to “As-Is” scenario. This implies that the implemented proposed heuristic minimised the idle time of operator 9 and increased utilisation. The overall implication of the results means that the implementation of the proposed heuristic to minimise operators and machines idle time is not effective when the demand is low and most especially when inventory levels are high or critical. In Figure 6.29 of the average order scenario, there are more operators over two shifts and more orders volumes engaged. As more disruptions set in during this period, there are more inventory borrow and hence more reasons to replenish provided there is available time and resources. Replenishment leads to an increase in total busy time operator on machine, if there is available time slot.

6.4.2 KPI 2: Resource Utilisation

The resource utilisation of flow-shop resources is also a significant key performance indicator. This is because the level of utilisation of flow-shop resources is directly proportional to the overall production performance in terms of processing time and total order produced per time. The performance of the flow-shop operation is determined through the usage of its resources. The resources usage is used to measure the efficiency and effectiveness of the proposed approach over the current production situation ("As-Is").

Apart from the events of disruption and the inventory association, it is essential to understand the impact of usage on this scenario. In Figure 6.31, the resource utilisation (usage) for high order under full, safe and critical inventory scenarios is represented. The figure shows the percentage usage over the 3 shifts period. The percentage usage of each operator is determined by dividing the total time with the total busy time multiply by 100 percent.

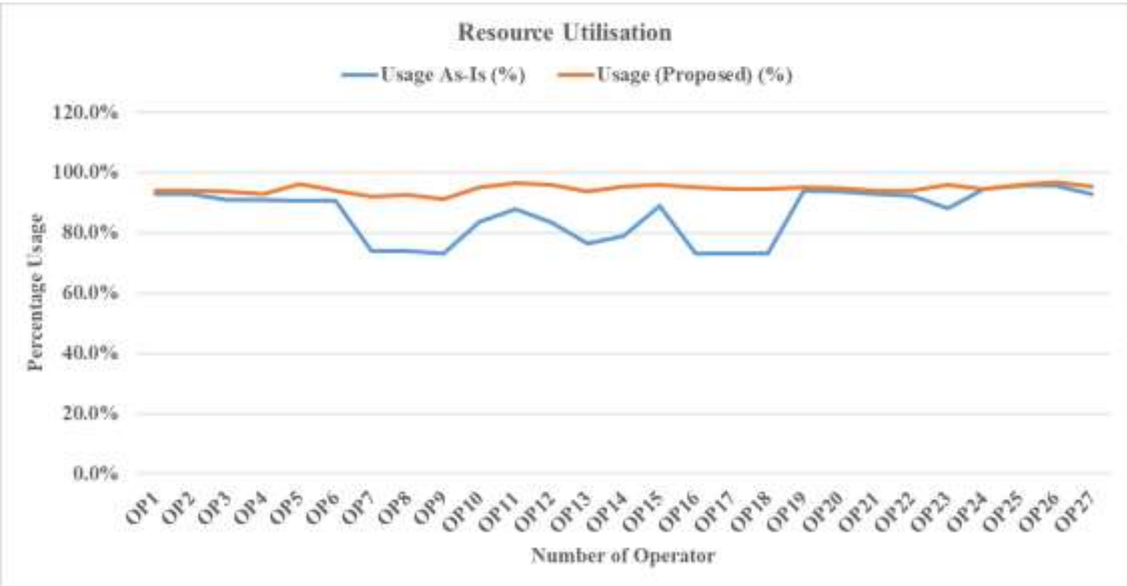


Figure 6-35: a.) Resource Utilisation comparison for high order full inventory scenario.

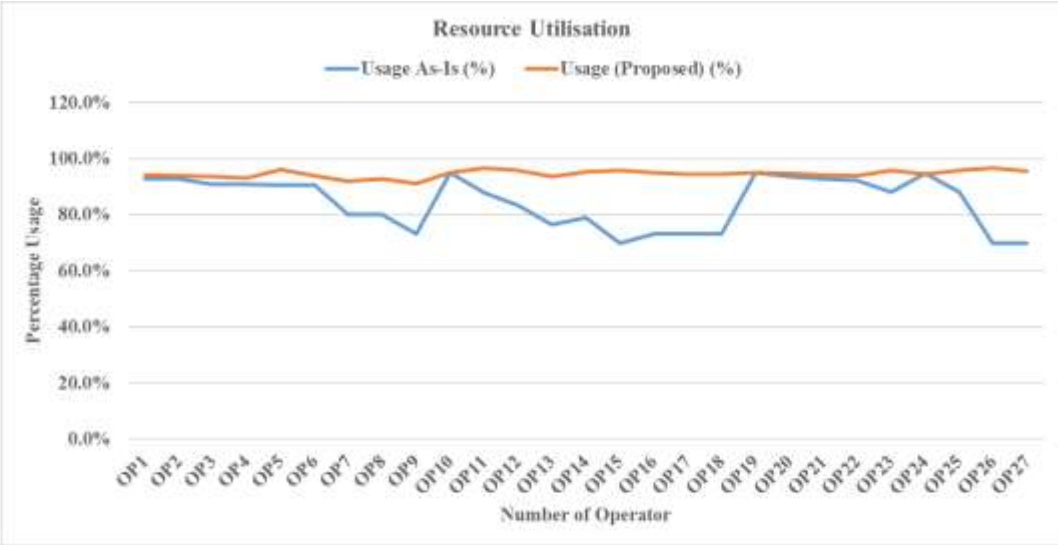


Figure 6-36: b) Resource Utilisation comparison for high order safe inventory scenario.

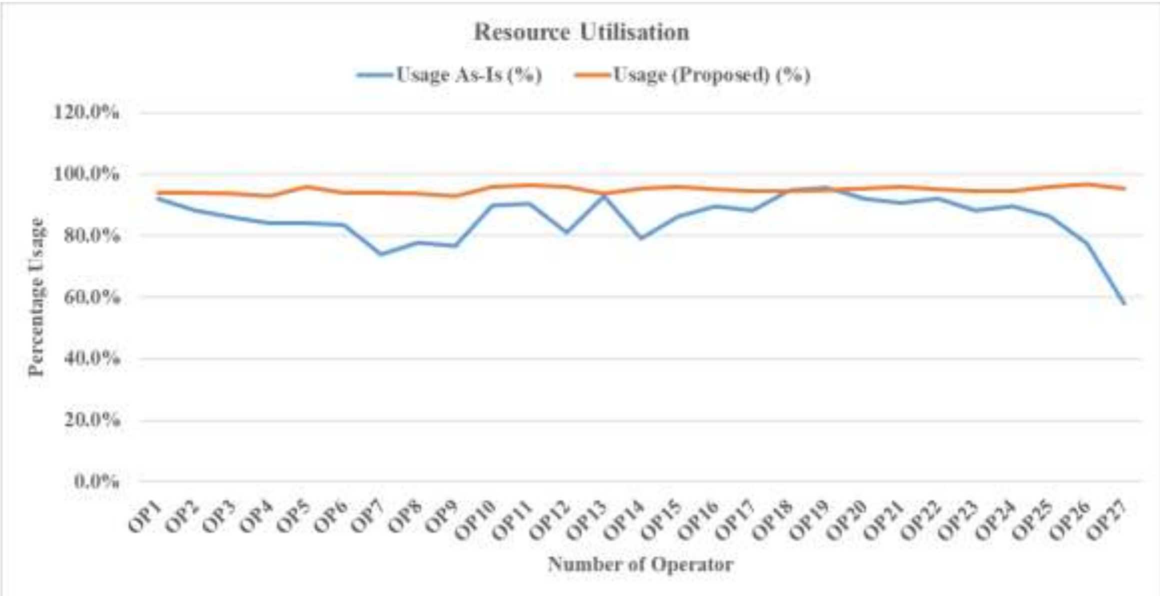


Figure 6-37: c) Resource Utilisation comparison for high order critical inventory scenario.

The system “As-Is” shows a continuous drop in the percentage usage for the safe and critical inventory scenarios during the first, second and third shifts. This is because there is higher idle time of operators in the 2 shifts. In the full inventory scenario of Figure 6.31a, the percentage usage seems slightly align for both as-is and proposed heuristic during the first and last shifts. It however dropped drastically for all operators during the second shift. This is reflected on the total usability of the production. In all cases, the proposed heuristic percentage usage maintained a steady state indicating maximum resources usage throughout the production processes. In Figure 6.28 of the high order volumes scenario, the operators’ time on machine is related to their utilisation as constraint to total production time, number of orders completed and the usability of the free time slot for replenishment. Even though the total busy time on machine for each operator forms one of the factors responsible for the resource utilisation trend, the amount of order completed, available time utilised for replenishment as well as idle time also contributes and impact the resources utilisation.

In Figure 6.32, the percentage usage of average order for high, safe and critical inventory scenarios is presented. The result is related to percentage usage of production resources during the two shifts period.

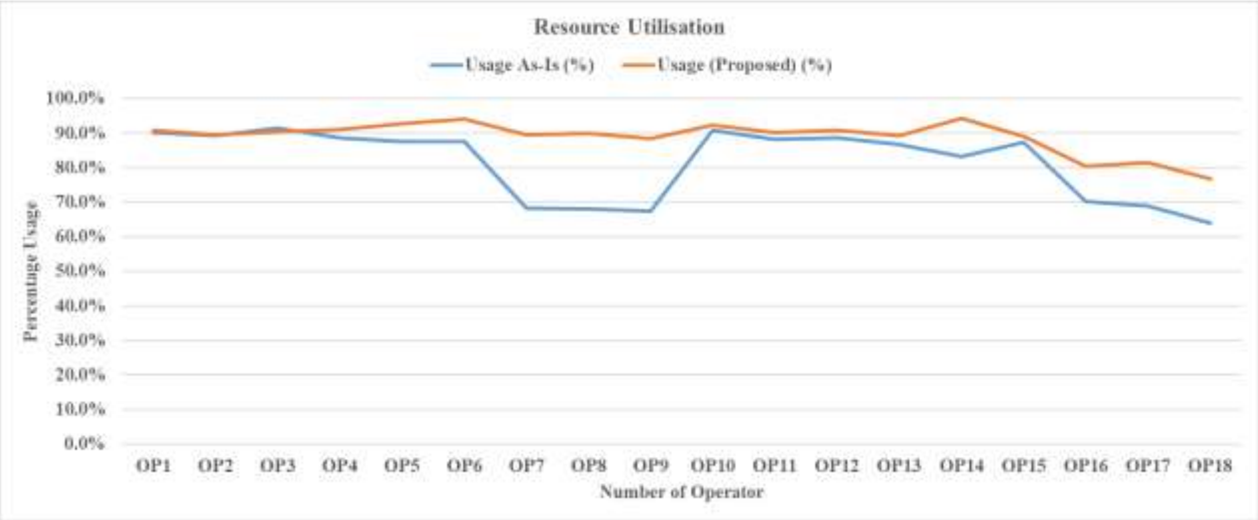


Figure 6-38: a) Resource Utilisation comparison for average order full inventory scenario.

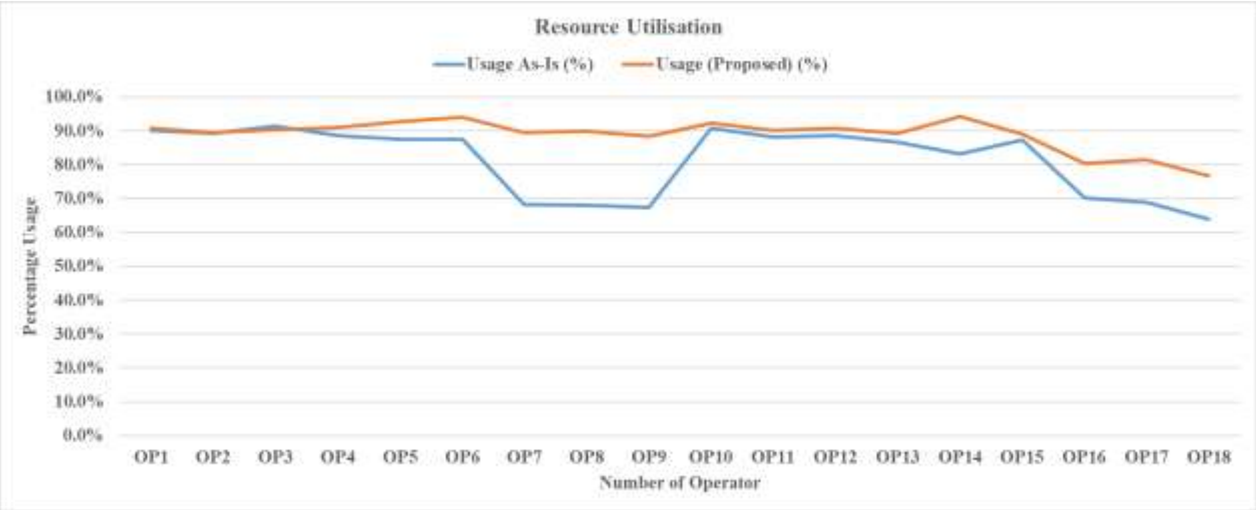


Figure 6-39: b) Resource Utilisation comparison for average order safe inventory scenario.

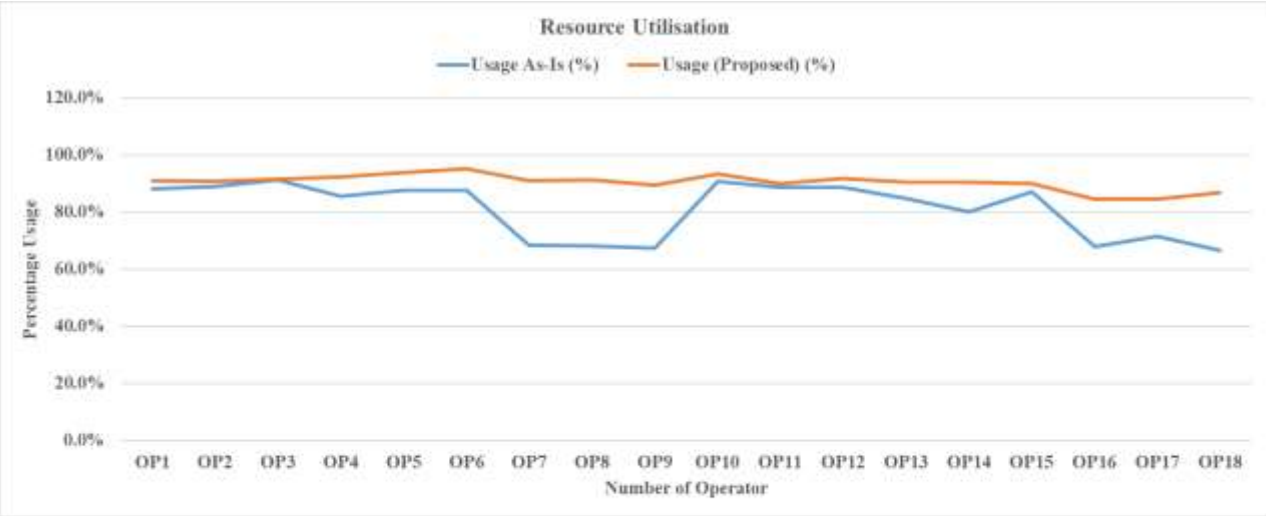


Figure 6-40: c) Resource Utilisation comparison for average order critical inventory scenario.

The resources utilisation trend of the average order volumes follows the same pattern for full, safe and critical inventory level. However, the differences showed a slightly varying production resources that is dependent on the type of disruption experienced. The obvious drop and immediate increase on operator 10 show a start of the second shift where percentage usage is at maximum for both “As-Is” and proposed heuristic. However, during the second shift the percentage usage behaves the same. This mean there is no direct implication on production. Although the percentage usage trends for proposed heuristic declined, it still shows significant improvement over the current situation of the flow-shop production. In Figure 6.29 of the average order volumes scenarios, the utilisation reflects operators’ time on machine as a major factor that influences production behaviour. Considering the inventory behaviour in this instance, the drop time and utilisation in both the “As-Is” and proposed heuristic in Figure 6.29 and Figure 6.32 explain why some inventory cannot be replenished even when there are time slots available. However, the proposed heuristic demonstrate superiority with both higher utilisation and operators’ time on machine. This implies that when the proposed heuristic is implemented, inventory is more maintained, and more orders get completed.

The percentage usage of low order scenario under full, safe and critical inventory level is depicted in Figure 6.33 below. This is related to single shift production period of 20 days.

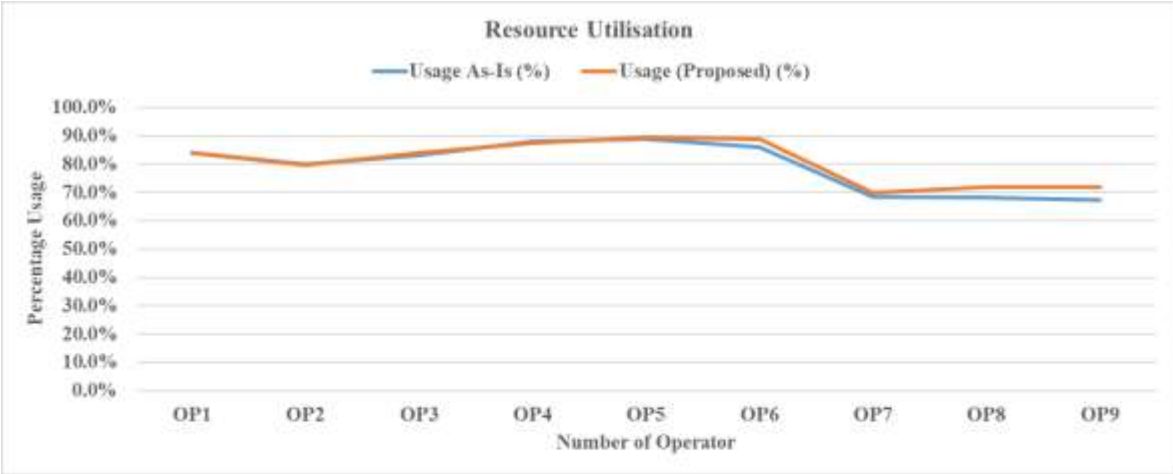


Figure 6-41: a) Resource Utilisation comparison for low order full inventory scenario.

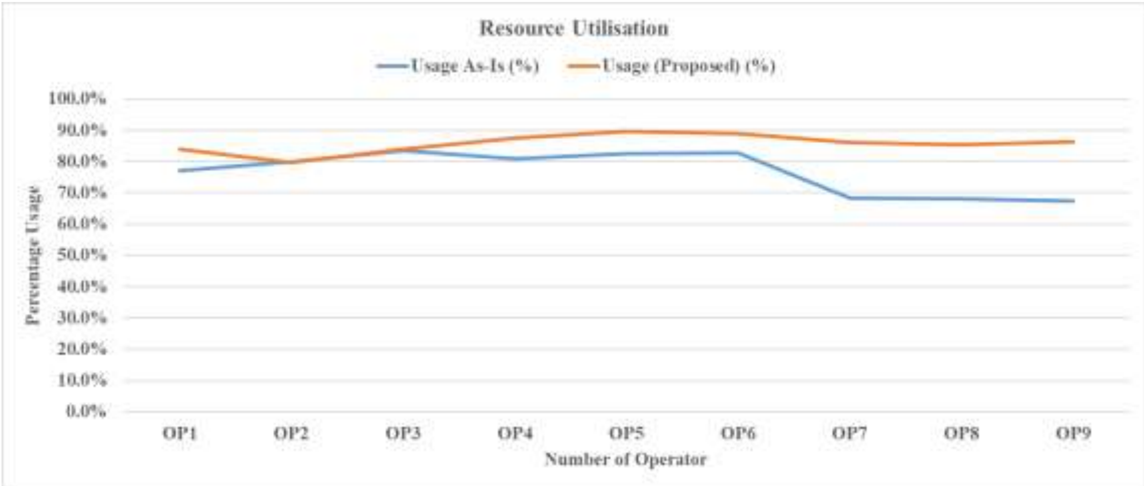
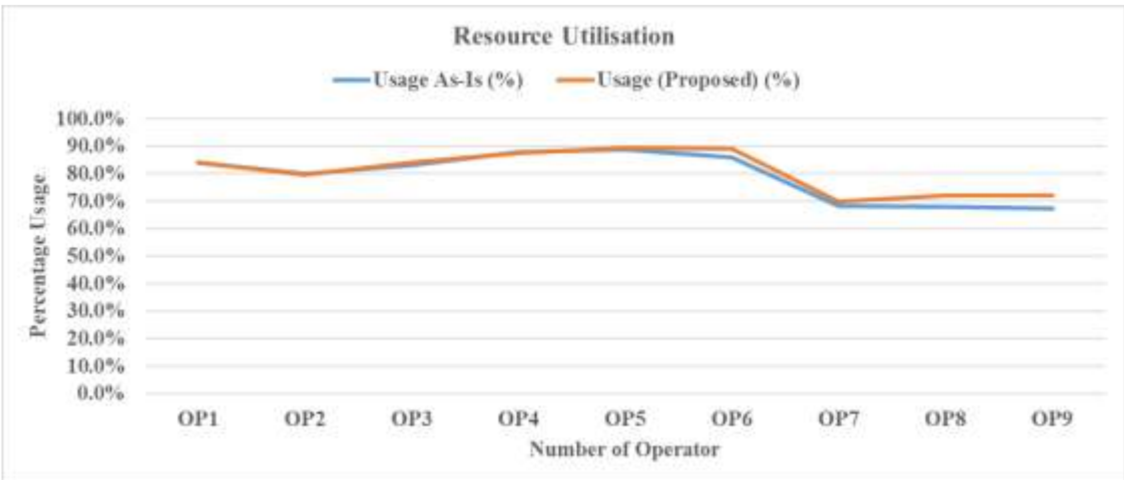


Figure 6-42: b) Resource Utilisation comparison for low order safe inventory scenario.



(c)

Figure 6-43: c) Resource Utilisation comparison for low order critical inventory scenario.

Similar utilisation trend is observed in Figure 6.33a and 6.33c as it appears that the proposed heuristic has little effect on the resource utilisation with low order volumes when inventory levels are full or critical. Meanwhile, in Figure 6.33b, an obvious different can be seen where the impact of the proposed heuristic appears to demonstrate higher utilisation level. This is evident judging by the inventory replenishment behaviour where sustainable inventory levels were maintained as shown in Figure 6.39b and 6.39c (discussed in Section 6.6). In some cases of the scenarios, there appears a drastic drop in resources usage percentage towards the end of the production shift. This can be associated with the inability of the corresponding operators to be assigned to machine for order processing resulting into higher idle times.

The steady trend in most part of the utilisation of resources indicates that resources are evenly utilised across all production process during the production period. On the other hand, there are drop in the utilisation of resources in some instances. This shows an uneven resource sharing, and as a result there is low utilisation of available resources. This suggests one of the reasons why some order production is not completed in due time and late/unsatisfied orders were recorded. As evident in the percentage usage results from all experiment scenarios, the proposed heuristic produces better results enabling the improved schedule and re-scheduling of jobs, operators and machines. It clearly shows reduction in the idle time by assigning tasks where there is 'available time slot' as proposed in this study. According to the Figure 6.30 results for low order volumes, the resources utilisation level behaves proportional to the amount of time operators spent on machines. This can be attributed to the lesser production scheduling stress and fewer number of disruptions in this instance.

6.4.3 KPI 3: Total Number of Late/Unsatisfied Orders

The total number of late/unsatisfied order is important when customer satisfaction is crucial. This is the case in this study. One of the purposes of the proposed approach is to continuously satisfy customer demand even in face of disruptions. Customer order satisfaction can be measured by the number of orders delivered and not completed. As KPIs, the number of late/unsatisfied orders is used to demonstrate the impact of the proposed heuristic on the flow-shop operation compared to the current state of operation ("As-Is"). In this simulation experiment, "As-Is" is the current approach used by the company. In order to represent the real-life inventory control, the "Full", "Safe", and "Critical" inventory denote inventory levels at 100%, above 50% and less than 50% limits respectively. In Table 6.28, the results of initially selected three order types is presented for all experiment scenarios.

Table 6-28: Total Late/Unsatisfied orders

Scenarios	Total Demand after Disruptions	“As-Is”	Proposed Heuristic
HF	4624	785	383
HS	4800	710	209
HC	4820	1152	675
AF	2471	164	0
AS	2579	205	33
AC	2547	248	153
LF	1215	0	0
LS	1283	0	0
LC	1261	15	0

The table highlights the total demand after disruptions for all scenario and calculate the total number of late/unsatisfied orders for both as-is and when heuristic is applied. For High order Full inventory (HF) 4624 order was requested of which 785 were not satisfied in as-is case while 383 was left unsatisfied. In this scenario, there is a late/unsatisfied order reduction of 402 when the proposed approach is applied. In the High order Safe inventory (HS) scenario, there are 4800 total customer demands after disruption. Only 209 were recorded unsatisfied under the proposed heuristic while 710 were not delivered by the production flow-shop ‘As-Is’. In High order critical inventory (HC) scenario, 1152 orders are late. Unsatisfied orders were recorded from 4820 total demand. Meanwhile 477 more orders were completed under the proposed heuristic approach. Likewise, in average order Full inventory scenario, out of 2471 total demand, no late/unsatisfied order was recorded under the proposed approach while 164 orders where late under the as-is scenario. In both average order safe and critical inventory scenario 33 and 153 orders were recorded late/unsatisfied under the proposed approach compared to 205 and 248 respectively under as-is condition. There was no late/ unsatisfied order recorded for both cases in the low order full and safe inventory scenarios. And the last

15 were recorded late for low order critical inventory as-is while proposed approach have none. Figure 6.34 shows a pictorial representation of the total late/unsatisfied orders for all scenarios.

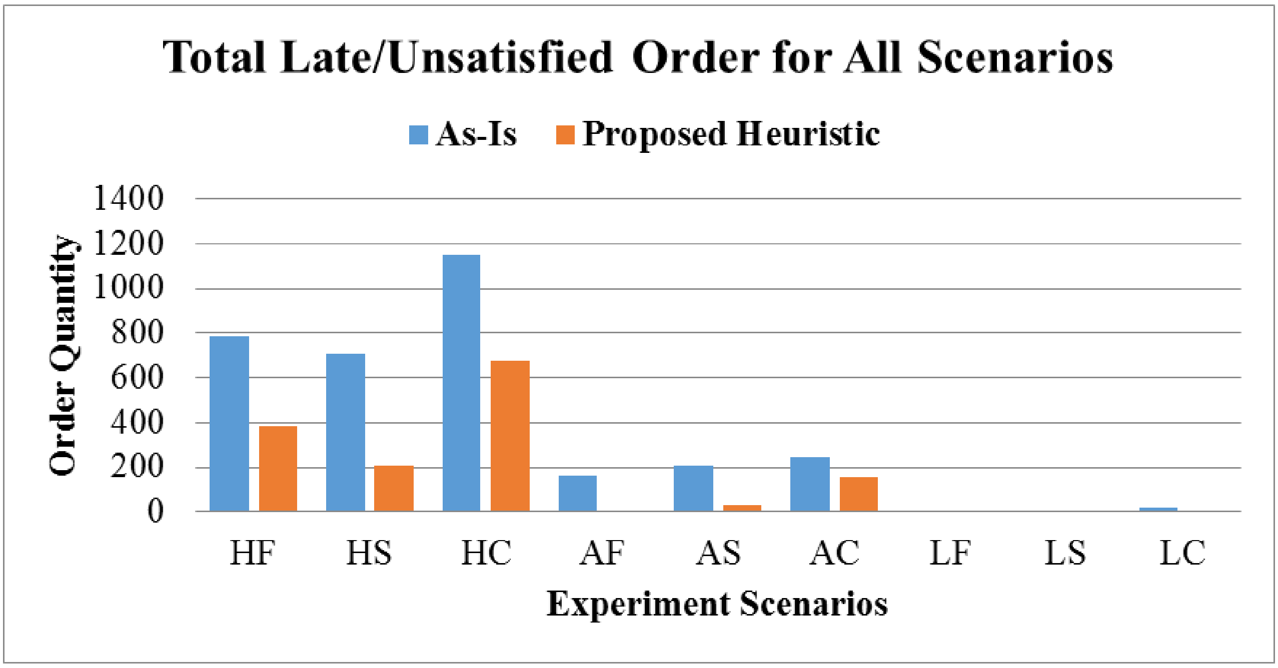


Figure 6-44: Total number of late/unsatisfied orders for all scenarios.

Although the proposed approach did not completely satisfy all customer demands, it demonstrates a significant improvement by reducing the number of late/unsatisfied orders in all cases.

6.5 Overall Inventory Behaviour

In Figures 6.35, the overall behaviour of the inventory "As-Is" and by applying the proposed heuristic algorithm can be observed for the 100 order types over the 20 days production period. As discussed in Section 3.5 of Chapter 3 of this report, the inventory replenishment strategy which demonstrates the gradual and non-instantaneous replenishment is shown in Figure 6.35. The graphical representation indicates inventory levels of all 100 orders "As-Is" and at the point replenishment when production period is completed.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Replenishment (After Heuristic)	23	16	0	50	60	60	75	54	5	0	15	78	45	48	89	0	36	75	26	0	0	10	0	15	12
Inventory (As-Is)	20	68	85	20	5	20	10	31	80	80	65	0	35	30	0	80	44	5	54	80	82	58	80	65	66

	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
Replenishment (After Heuristic)	48	78	78	59	65	12	0	0	0	0	0	0	66	25	15	90	45	12	0	0	50	12	20	45	0
Inventory (As-Is)	30	0	0	20	13	66	80	85	85	0	12	0	0	20	51	0	32	53	78	67	0	55	60	0	60

	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
Replenishment (After Heuristic)	0	60	56	75	41	52	30	30	30	6	54	52	0	0	0	0	40	45	25	15	64	75	36	34	82
Inventory (As-Is)	75	0	0	0	24	0	45	45	45	46	0	0	80	88	0	0	0	0	38	49	0	0	20	0	0

	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
Replenishment (After Heuristic)	51	16	78	48	51	20	20	50	34	20	12	56	0	0	0	0	54	0	0	10	48	0	0	15	15
Inventory (As-Is)	0	48	0	0	0	64	36	28	30	62	75	0	87	82	90	90	28	82	87	80	0	80	74	40	50

Figure 6-35: The Overall inventory replenishment for "As-Is" and after the proposed heuristic.

From the Figure 6.35, the "blue bars" indicate inventory levels of each of the 100 orders at the end of production under current "As-Is", that is the flow-shop current operations. It is not a progressive trend of inventory a particular order. Also, the "Orange bars" indicate the "improved" inventory levels of each of the 100 orders when the proposed heuristic was applied. Under the flow-shop current operation, borrowing from inventory is not used as a strategy to tackle disruption. But rather a normal keeping of inventory which is always at critical level because of production backlogs caused by disruption.

The idea of maintaining sustainable inventory level based on production shortage need is revealed. However, in some cases where inventory appear lower (as the case of 39, 46 and 74) means some of heuristic conditions that control the replenishment were not met. These conditions include the following;

- Machine and operator availability for available time slot used for replenishment.
- Available time slot enough for order quantity awaiting replenishment.
- The similarity of the order types machine setup in between the available time slot.

In Figure 6.35, the proposed heuristic implementation tries to balance the inventory level gradually based on non-instantaneous condition mentioned in chapter 3. This is to offer all order types opportunity to support production shortages when there are disruptions. In the replenishment condition, the order type with the lease inventory is considered first while orders at the same inventory level are considered based on time-sharing random replenishment. However, in some cases orders with the least levels are left without being replenished. This is due to non-satisfaction of all replenishment conditions or lack of available time slot suitable for the specific order type.

Table 6.29 below presents the comparison results of three approaches, the proposed heuristic, "As-Is" and the sequential replenishment approach.

Table 6-29: Approaches Comparison based on Late/Unsatisfied orders

Scenarios	Total Demand after Disruptions	"As-Is"	Sequential	Proposed Heuristic
HF	4624	785	521	383
HS	4800	710	408	209
HC	4820	1152	1005	675
AF	2471	164	125	0
AS	2579	205	384	33
AC	2547	248	254	153
LF	1215	0	0	0
LS	1283	0	0	0
LC	1261	15	0	0
Standard Deviation		416	329	**233**

The results are compared based on the changes that occurred in term of total demand after disruptions. In order to determine the level of dispersion, standard deviation of each of them is calculated. Among the three, the proposed heuristic have the smallest number at 233, which implies less dispersion and therefore more effective.

In the next section, the behaviour of order inventory is compared over the production period.

6.6 Inventory Level Behaviour Comparison

In this section, the behaviour of the "As-Is" inventory levels are compared with sequential replenishment method and the proposed heuristic replenishment. The discussion of this behaviour is combined for all experiment scenarios. The selected comparison approach is used to determine improvement and justify the effectiveness of the proposed approach based on the behaviour of the inventory. The sequential approach tends to replenish inventory successively while the proposed approach replenished inventory based on the predefined rules which ensure sustainable level of inventory for all order types. In Figure 6.36 below, the inventory level for high order of full, safe and critical inventory for all order types is depicted.

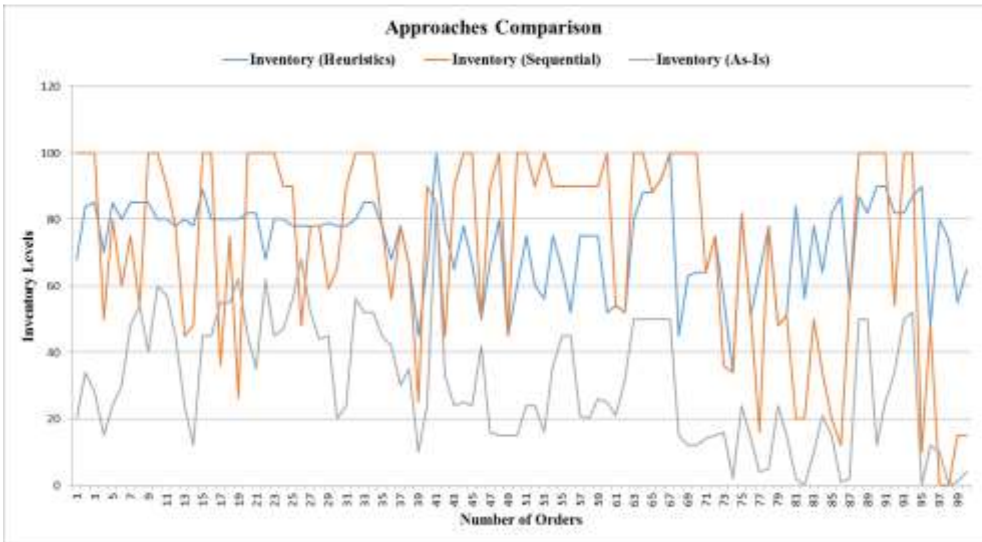


Figure 6-45 a) **Inventory behaviour comparison for high order vs full inventory.**

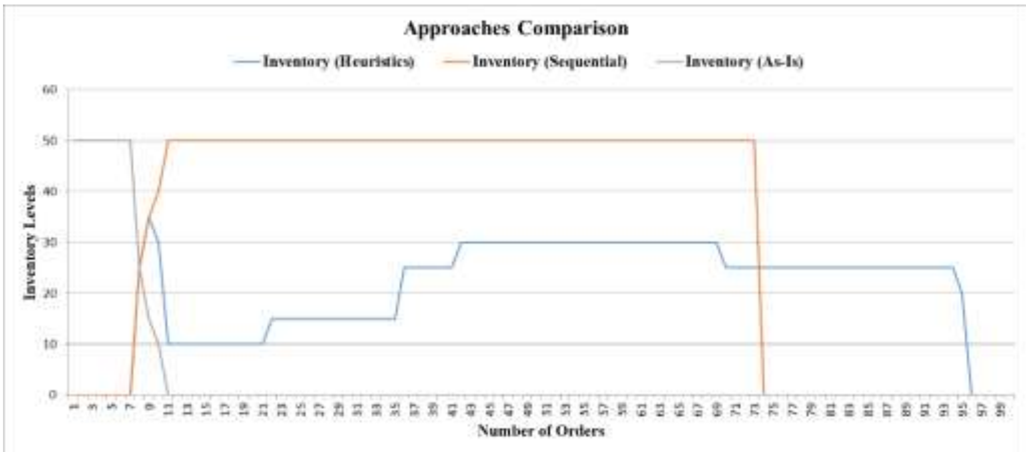


Figure 6-46: **b) Inventory behaviour comparison for high order vs safe inventory**

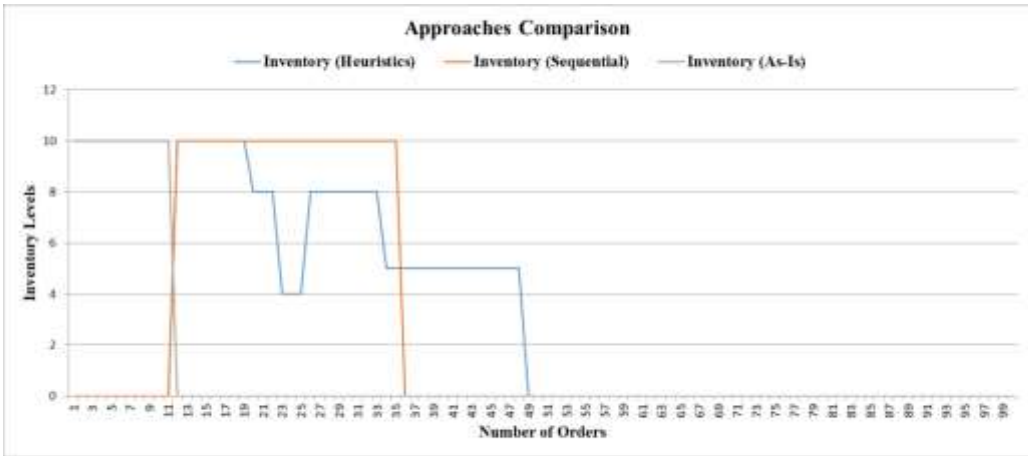


Figure 6-47: c) **Inventory behaviour comparison for high order vs critical inventory.**

Figure 6.36a shows a rather interesting trends of inventory behaviour for all approaches. When the "As-Is" is down, the proposed approach appear to maintain the middle, indicating there is no drastic replenishment attempt to the maximum on order neglect. The sequential approach for replenishment in this scenario hits the maximum level in some cases hereby ignoring some order which remains at least level. For instance, order 40, 76 and 94 to 100 are all not replenished at the same level with the likes of 1-2, 9-11, 19-24 which are all replenished sequentially to the maximum level. This implication of the sequential approach is keeping too high inventory levels which are unnecessary at the expense of orders are close to zero levels.

In both Figure 6.36b and c (blue line), the proposed approach demonstrates a sustainable way of keep useful inventory limit rather than unnecessarily building up inventory levels. The gradual build-up of inventory is the confirmation of how inventory replenishment is approach. On the other hand, the sequential approach maintained the peak for both safe and critical level at the initial stage, but the approach makes free time slot for replenishment insufficient. The idea of proposed approach helps maintain balance for a greater number of orders than the sequential method. The more the number of order inventory maintained, the more order availability for production support.

In Figure 6.37, the inventory behaviour comparison for average order under full, safe and critical inventory is presented.

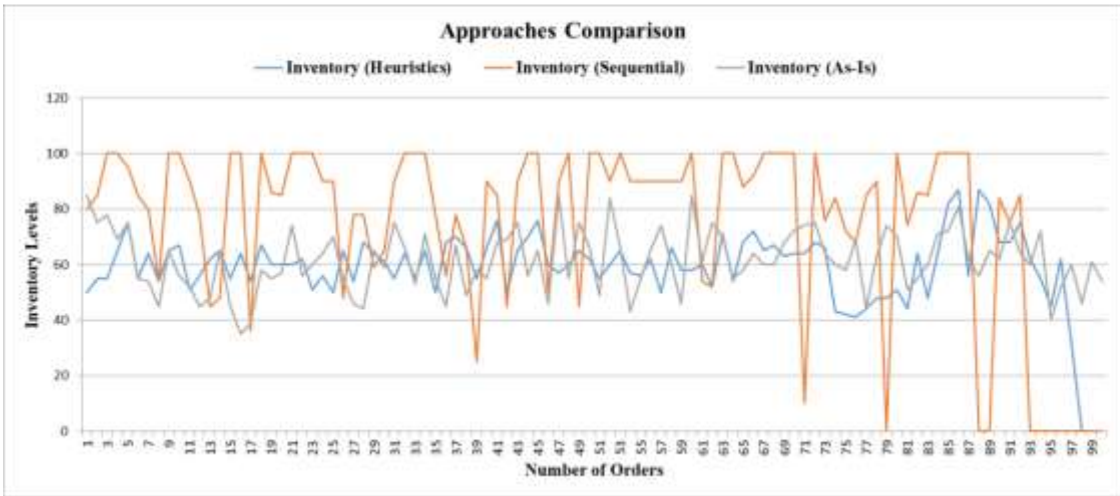


Figure 6-48: a) Inventory behaviour comparison for average order vs full inventory.

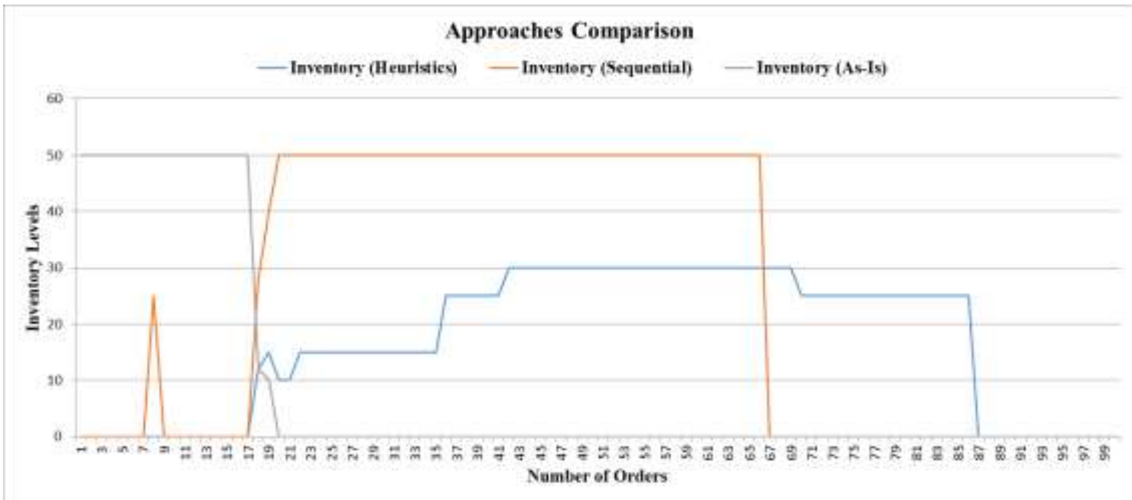


Figure **6-49**: **b)** Inventory behaviour comparison for average order vs safe inventory**.**

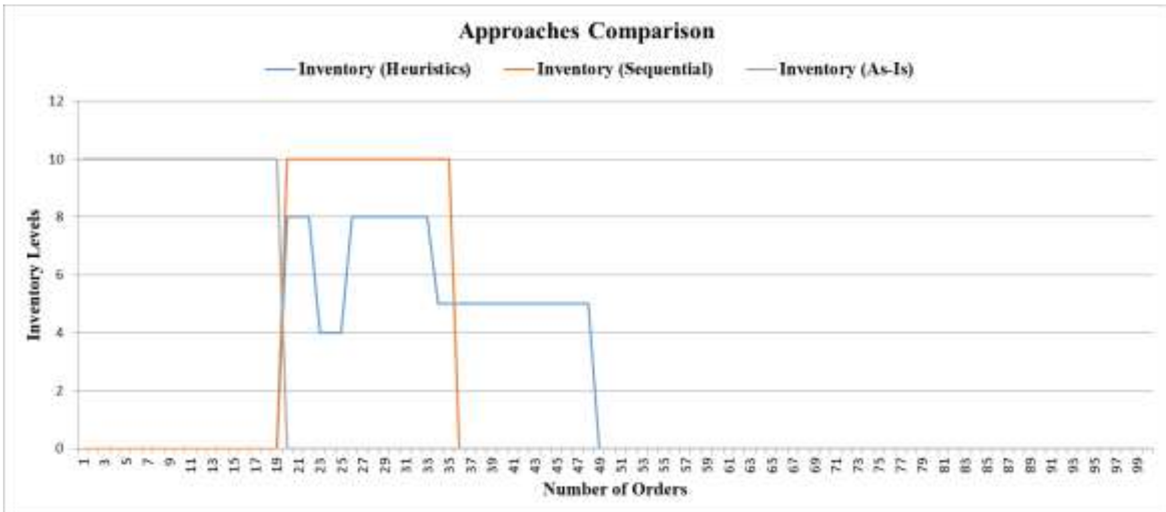


Figure 6-50: c) **Inventory behaviour comparison for average order vs critical inventory.**

In Figure 6.37 of average order full inventory level, as the actual ("As-Is") inventory drops for each order types which the proposed heuristics approach try to maintain to an even distribution and non-biased time-sharing replenishment of order. This was achieved to prevent neglecting the replenishment of some order types that might be required for production support. This was not the case for sequential replenishment which focuses on replenishing order inventory to the maximum level possible. For this reason, sequential replenishment approach left more orders at the least level because of time shortages. In Figure 6.37c for sequential approach, orders 53 to 100 was not replenishment as the replenishment measure only favours orders 6-12, 34-46 and 48-51.

In Figure 6.38, the inventory behaviour with low order under high, safe and critical inventory levels is shown.

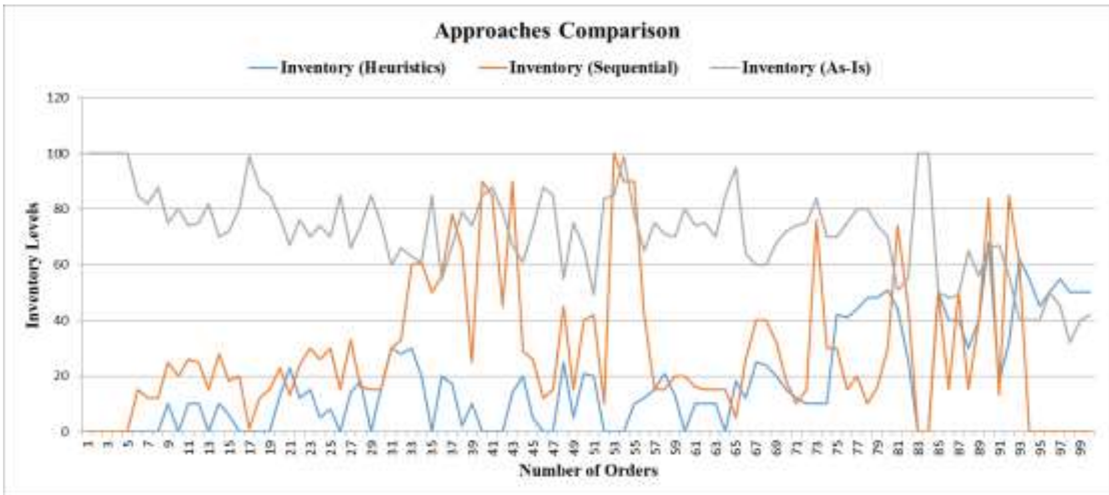


Figure 6-51: **a) Inventory behaviour comparison for low order vs full inventory**.

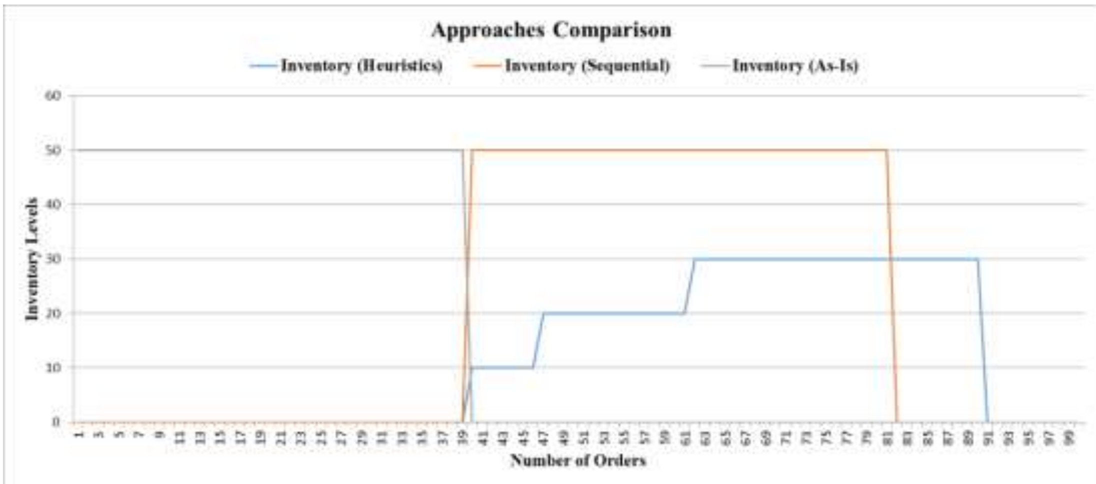


Figure 6-52: b) **Inventory behaviour comparison for low order vs safe inventory**.

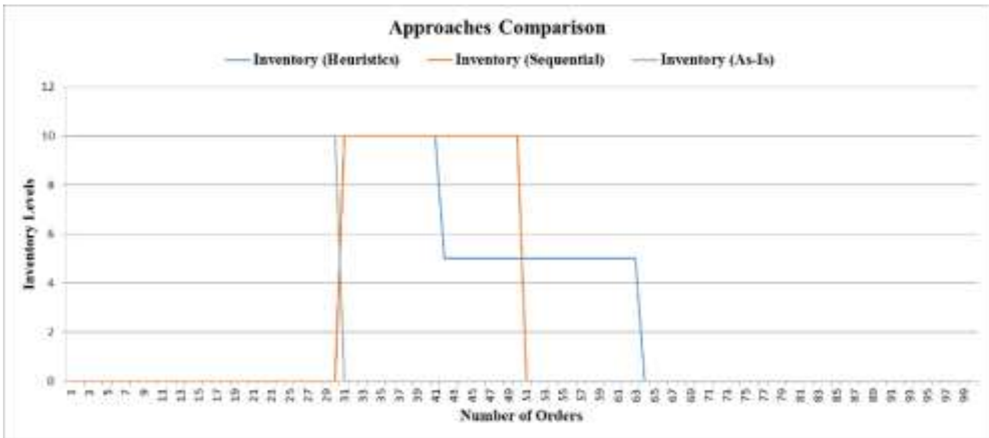


Figure 6-53: c) **Inventory behaviour comparison for low order vs critical inventory.**

In Figure 6.38 for the low order high, safe and critical inventory, the proposed approach is seen maintaining a sustainable level of all order inventories especially for Figure 6.38b and c. The consequence of this sequential replenishment approach is keeping unnecessary level of order inventory when they are not needed. Like Figure 6.38b show a case unnecessary inventory levels for sequential approach. More interesting in Figure 6.38a for the proposed approach, the replenishment trend is lowered to balance the inventory as most of as-is order inventory levels are close to maximum level. In these scenarios, the sustainable effect of the proposed heuristic approach is evident. The proposed replenishment approach impacts more orders in a more balanced way to ensure overall support for production. When there are disruptions on the flow-shop, sequential approach is likely to record higher number of unsatisfied orders. This is because focuses on sequential replenishment of order to the maximum level rather considering the impact of disruption on order satisfaction.

In Tables 6.30 to 6.32, the two approaches and the "As-Is" scenario are compared by taking the standard deviations of their mean-based inventory level behaviour.

Table 6-30: Comparison for High Order Volumes

Standard Deviation			
Scenarios	**"As-Is"**	**Sequential**	**Proposed Algorithm**
HF	18.9	29.5	13.3
HS	21.2	29.5	13.3

HC	16.4	14.3	13.3

Table 6-31: Comparison for Average Order Volumes

Standard Deviation			
Scenarios	**"As-Is"**	**Sequential**	**Proposed Algorithm**
AF	21.2	29.5	13.3
AS	13.7	13.2	11.5
AC	21.2	29.5	13.3

Table 6-32: Comparison for Low Order Volumes

Standard Deviation			
Scenarios	**"As-Is"**	**Sequential**	**Proposed Algorithm**
LF	4.22	4.11	1.28
LS	4.22	4.11	1.28
LC	4.22	4.11	1.28

The standard deviation measures the dispersion of the results of all the scenarios. The effectiveness of the proposed heuristics is shown by less dispersion of the results obtain particularly in table 6.30 for high order volumes and Table 6.31 for average order volume scenarios. In Table 6.32 for low order volumes, the proposed heuristic is does not make any different with both "As-Is" and the sequential method. However, the proposed heuristic performs effectively well compare to the two scenarios under high and average order volumes.

6.7 Chapter Summary

In this chapter, the analysis and discussion of the different categories of the experiments were presented. The simulation experiments demonstrate the implementation of the proposed re-scheduling heuristic for production support and inventory replenishments. This was tested with the random combination of disruption under different demand and inventory level behaviours. The effectiveness of the proposed heuristic approach was determined by three KPIs; operation total time on machine, percentage usage and total number of late/unsatisfied orders. The results revealed that adaptive response to disruptions is more sustainable with enough level of inventory support, especially for high and average order volumes. It is also important to note that other flow-shop activities and utilisation of resources contribute significantly to achieving successful implementation of the proposed heuristic. The proposed approach achieved better results with high and average order volumes. And most especially, in average order volumes with high inventory, as this is the situation that sufficiently demonstrate the strategy explained in the methodology Chapter 3. The study emphasises sustainable inventory level to continually support production shortages. This is in quest to satisfy customers' demand to the optimum, even when there are disruptions affecting production process. In Figures 6.21 to 6.27, the system demonstrates the non-instantaneous inventory replenishment by taking into consideration inventory levels as proposed in the heuristic steps. This is shown using arrows indicating the level of inventories of the selected orders when replenishments take place. This is compared with the level of inventories of other orders to clearly justify the need for replenishment and why an order is not replenished. In Tables 6.21 to 6.27, number of cancellations which create available time for replenishment is indicated. In some cases, even though there are cancellations, available time might not suffice due to the impact of other disruption occurring at the same time. That explains why there are late/unsatisfied order in Table 6.17 even when there are order cancellations. Ultimately, the proposed heuristic has shown its most effective impact on the scenarios where there are high and average order volumes with critical and safe inventory respectively. For low order volumes at all inventory categories, the proposed heuristic has minimal effect and does not suggest any improvement expected.

The comparison of the proposed method with the sequential method in terms of inventory replenishment indicate more sustainable impact. The proposed method is more effective in responding to disruption through the inventory replenishment strategy. Compared with the sequential replenishment which, although tries to replenishment the inventory to the maximum levels, failed to balance all inventory levels in a sustainable manner. In this regard, the proposed method recorded fewer late/unsatisfied order than both sequential and as the current system situation ("As-Is").

Chapter 7: Conclusion and Recommendation

7.1 Introduction

This chapter concludes the main context of the thesis by reviewing the work that has been done, discusses lessons learned as a result. Then attempt to put the research into perspectives, and finally providing some directions to potential future areas of research. In this thesis, attempt has been made to identify knowledge gap (in Section 2.6) based on review of the selected literature. The study established that customer-related or customer-imposed production disruptions are prominent and impact OEMs flow-shop performance. Even though the problems relating to flow-shop manufacturing has been widely researched. The issues of disruptions emanating from customers has not been given enough attention which this research offered. Equally, numerous approaches and algorithms have been developed to tackle disruption problems in flow-shop setting. But none suffice for the types of disruptions combined in this study, especially implemented for OEMs flow-shop under customer (automotive assembly line) influence. The highlights of the study are summarised in this rest of the sections as well as the research objectives realisations.

7.2 Conclusion for the OEM Flow-Shop System

The OEMs flow-shop system environment was simulated within excel spreadsheet using VBA programming. The chosen tool, platform and programming language selection is due to their compatibility which also suits the research problem situation (Robinson 2004). Based on the review, agent-based simulation has been modelled in spreadsheet, using VBA programming language instead of specialist simulation software. The strength of programming language was analysed in terms of flexibility, and adaptability with the problem complexities. In terms of ease of usage and validation, specialist simulation software is said to be suitable. However, the rigid nature of specialist software made it unsuitable for the complex and dynamic nature of the OEM flow-shop production entities and environment under disruptions. The system was positioned with the problem and operated in this manner of consequences.

- Disruptions cause late/unsatisfied orders, inventory is introduced as production support strategy.
- Disruptions create idle time which are utilised for inventory replenishment for continual support.

Overall, the developed simulation system was implemented successfully with the following functions:

- Optimise the utilisation of production resources.
- Check late/uncompleted order and borrow from inventory.
- Reschedule order processing during disruptions.
- Reallocate idle machine and operator to waiting orders.
- Utilise idle times as replenishment opportunity.
- Provide production evaluation in terms of key performance indicators (KPIs).

7.3 Conclusion from Literature Review

The literature review, as stated in Section 7.1, was the basis for the identified gap in knowledge. The review of related works discussed in Sections (2.3, 2.4 and 2.5) contributed to the selected approach used to solve the disruption problems. The findings from the number of related literatures in this study brought about research positioning and support in different ways. It provided this study with the needed theoretical background. For this reason, linkage was established between the proposed approaches with the existing studies. The findings from literature has been used to position the contribution of the current study to existing body of knowledge. It helps the research outcome being integrated into academic and industrial body of knowledge.

Apart from using the existing works to establish the research problems, it helped shape it. The OEMs industry clearly identified has an area within manufacturing and supply chain sectors and the focus was on its flow-shop production disruptions. The knowledge of the research area through review made it possible to streamline a broad industry to a precise target which gives this study clear direction in OEMs. In terms of the research methodology, the literature review offered knowledge of the simulation methods, heuristic algorithms and inventory models used like the proposed one. And through the understanding of the positioning of the existing methods, a new adaptive approach is proposed in this study for the problem nature.

7.4 Agent-Based Simulation Conclusion

Simulation models are common and have been widely used in flow-shop industry to evaluate production line performance and to improve their efficiency (Sieber et al. 2010). Based on the current study experience, researchers tend to fit in well known technique into their research problem. Choosing simulation method can be associated with finding suitable means of mimicking reality. This means the best means should achieve the best results. However, simulation technique is considered appropriate when it is based on research problem requirements rather than factors like availability or researchers' knowledge of it. Although Discrete Event Simulation (DES), System Dynamic (SD) and other traditional modelling techniques are common in flow-shop and manufacturing context, they do not fully address the research problem requirements. For this reason, agent-based simulation method was preferred in this study compared to other simulation methods for the following reasons:

- The real-life case study situation of the disruption problems was best understood with the application of agent-based simulation approach, because of the process interaction associated with it, which is well suited for agent-based method.
- Agent-based method is more associated with complex and dynamic problems as it is the case in this study.

- For flow-shop production entities to interact, react and share information autonomously within the system operation, agent-based simulation is the obvious choice.
- Most importantly, agent-based simulation was applied the disruption problem because the past (initial demand) is not a predictor of the future (actual demand).

7.5 Production Disruption-Inventory Replenishment (PDIR) Framework Conclusion

Going by the PDIR Framework that have been proposed in this thesis. It was successfully implemented in this research and guided the experiments procedures. There are records of various frameworks proposed by research in this area. But the proposed PDIR Framework is different for the integration of the three modules and the strategic concepts within. The agent-based simulation, adaptive heuristic algorithm and the associated inventory control are significantly peculiar to the disruption problems in OEMs industry. The framework characterised problem situation or production settings where customer assembly lines are on constant standby waiting for OEMs production delivery per time.

The in-depth understanding of the importance of the problem nature in the development of the resolution framework brought out the developed PDIR framework. Even through the proposed PDIR framework has been utilised to solve disruption problems identified in this study. It has not been regarded as complete formation for problem resolution, as their opportunities for improvements. The impact of the framework was known as it was tested for the highlighted list of scenarios described in Section 6.2. It has also been implemented for the combination of the three disruptions that have been considered. The behaviour of the framework for any other problem definition is however unclear until experimented.

7.6 Conclusion on the Experiment KPIs

The effectiveness of the proposed approach has been quantified using three KPIs; the operators' total time on machines, resource utilisation, and total number of late/unsatisfied orders (Section 6.4). These selected KPIs are relevant because machine and operation interacts with order processing in the OEMs flow-shop. The relationship has been used to assess the utilisation of performance of the flow-shop, as it determined the number of late/unsatisfied customer orders. Particularly, the number of late/unsatisfied orders is significant KPI in the OEMs flow-shop production. This is because the goal of the production decision maker is to satisfy customer demands in terms of quantity of order production and delivery.

7.7 Lesson Learned from the Experimentations

The experiments demonstrated the implementation of the proposed heuristic algorithm as applied in agent-based simulation to mimic OEMs flow-shop under disruptions condition, where inventory is introduced as production shortages support. There are number of lessons learned and knowledge gained from the experiments. In Section 6.2, nine experiment scenarios were formulated for the OEMs flow-shop. And random combination of the three disruptions were tested for each scenario.

- High order volume vs Full inventory level (HF).
- High order volume vs Safe inventory level (HS).
- High order volume vs Critical inventory level (HC).
- Average order volume vs Full inventory level (AF).
- Average order volume vs Safe inventory level (AS).
- Average order volume vs Critical inventory level (AC).
- Low order volume vs Full inventory level (LF).
- Low order volume vs Safe inventory level (LS).
- Low order volume vs Critical inventory level (LC).

Among all the scenarios experiment conducted, high and average order volume with all inventory categories appeared to be suitable for the proposed approach as shown in Chapter 6. Average order volume scenarios appear to support the proposed integrated heuristic algorithm, inventory and simulation approach (Section 6.3.4- 6.3.6) the most. This is because, the results of the scenario demonstrated promising behaviours of the flow-shop under disruptions. Meanwhile, the impacts of the proposed approach for the low order volume are not visible (Section 6.3.7- 6.3.9). The production and the inventory behaviour are steady and not affected by disruptions. For this reason, proposed approach might not be suitable for low customer order volumes. However, it is useful to investigate with varying simulation parameters to gain further knowledge of how the system would behave under low order volume situation.

7.8 Lesson Learned from Comparison of Approaches

The proposed approach was compared with the current flow-shop situation ("As-Is") of the case study and the sequential method. The choice of "As-Is" scenario was used as benchmark for improvement. However, the sequential method is considered appropriate for comparison under this problem and solution circumstances. Although there are other available methods to select, however, they deemed inappropriate. This is because the problem nature and key elements of resolution need to correlate for fair judgment of approaches. Other available approaches deviated from key outcomes of interest that are considered in this study. The lesson learned from the comparisons are as follows:

- The proposed approach provided more production performance improvement in terms of number of late/unsatisfied customer orders. For instance, in Table 6.29, for high order volume and full inventory level (HF), only 8.28% of the total demanded order were late/unsatisfied using the proposed heuristic approach while 11.27% and 16.98% were recorded for sequential and "As-Is" respectively.
- Using the proposed approach, there are less operator-machine total idle time compared to the two "As-Is" scenario and sequential approach. For instance, in Figure 6.28, for high order and full inventory, for one machine-operator, the total busy time was 8344 minutes out of the available 8700 minutes when the proposed heuristic approach was applied. While 7744 minutes with "As-Is" scenario.

- In the inventory, the proposed heuristic for replenishment demonstrated a sustainable trend (Figure 6.37) which is healthy for continuous production support, compared to the sequential approach and “As-Is” scenario.

7.9 Meeting the Research Objectives

This section demonstrates how the research objectives highlighted in section 1.7 have been achieved.

1. In Chapter 2 literature review sections, related studies focusing on disruption in flow-shop related environments were reviewed. And various approaches used to solve them in terms of agent-based, heuristic and inventory control were discussed.
2. In Chapter 4 of modelling specification, different related logics and illustration were identified and designed to understand problem details. Also, in chapter 5, case study representation of the real-life OEMs flow-shop was depicted using different logical diagrams.
3. Details of the case study data collection for the purpose of experimentation was reported.
4. In Chapter 3 and 4, modelling methodology and specifications was discussed, with agent-based procedures and diagram showing the simulated system has been presented.
5. Specifically, in Section 3.5, the proposed adaptive heuristic algorithm was presented showing step by step process for disrupted flow-shop resolution.
6. In Chapter 6, the demonstration of the proposed approach in form of framework was presented through different scenario experiments under different disruption.
7. The proposed PDIR framework in Figure 3.2 demonstrate the delivery of the objective for integrated methods for solving disruption problems.
8. Suitable OEMs flow-shop case study was selected, and real-life data was obtained to verify the developed model. While industrial experts’ approval was relied on for model validation.

7.10 Research Limitations

Limitations arose since no solution approach or method fits all problems possibilities. As the research attempted to tackle customer-imposed production disruption in OEMs flow-shop, there are limitations.

- The proposed framework, in which the heuristic, agent-based and inventory are embedded, is applicable for flow-shop production where customer influence act as a push that disrupt initially scheduled production processes.
- In flow-shop setting, the cost of holding inventory, and unsatisfied orders are significant to performance estimation. Cost function has not been considered in the developed approach, but rather the inventory was utilised as strategic means of dealing with disruptions and satisfying customer orders.

7.11 Recommendations for Further Research

Due to research limitations, this research cannot be considered exhaustive. But it has opened many interesting aspects to be addresses, particularly on various disruptions, their causes and how to use them as opportunity to improve OEMs flow-shop industry. Likewise, the proposed framework approach is not 'all-sufficient', even for the specific OEMs flow-shop disruption problems. Therefore, recommendations for further research are suggested as follows:

- In addition to the disruption considered, other types of disruptions associated with flow-shop can be researched.
- It would be interesting to further study the cost impacts of the system under different scenarios.
- This study is based on flow-shop, further research can be considered for open shop, job shop scheduling under the same disruptions combinations.
- The research experiments can be tested for more combination of additional scenarios under different simulation rules and also the results can be compared with other related approaches.
- In terms of inventory control, different other replenishment policies associated with manufacturing production can be tested.

- The research model can further be extended to incorporate supply chain system to widen the impacts of customer-imposed disruptions.
- Likewise, other meta-heuristics approaches such as swarm optimisation, genetic algorithm can be applied to optimise production performances.

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Appendix

Table 1: Machine – Operator "As-Is" Utilisation for high order vs full inventory

Operator	**Shift**	**Total Time (Mins)**	**Idle Time (Mins)**	**Setup Time (Mins)**	**Total Busy Time (Mins)**	**Time on M1**	**Time on M2**	**Time on M3**	**Time on M4**	**Time on M5**	**Usage (%)**
OP1	1	8,700	187	428	8085	1637	2044	1560	1744	1100	92.93%
OP2	1	8,700	142	480	8078	1835	1635	1637	1658	1313	92.85%
OP3	1	8,700	359	428	7913	1637	1602	1584	1602	1488	90.95%
OP4	1	8,700	362	428	7910	1802	1602	1602	1502	1402	90.92%
OP5	1	8,700	549	256	7895	1679	1576	1420	1668	1552	90.75%
OP6	1	8,700	565	256	7879	1575	1957	1637	1675	1035	90.56%
OP7	1	8,700	1841	428	6431	1637	2044	1560	1190	0	73.92%
OP8	1	8,700	1841	428	6431	1838	2044	1602	947	0	73.92%

OP9	1	8,700	1841	490	6369	1835	2044	1602	888	0	73.21%
OP10	2	8,700	1001	428	7271	1528	1454	1531	1130	1628	83.57%
OP11	2	8,700	568	480	7652	1952	1290	1560	1200	1650	87.95%
OP12	2	8,700	1020	428	7252	1650	1542	1530	1320	1210	83.36%
OP13	2	8,700	1562	490	6648	1485	1325	1425	1200	1213	76.41%
OP14	2	8,700	1562	256	6882	1984	1565	1425	1130	778	79.10%
OP15	2	8,700	528	428	7744	1548	1650	1550	1340	1656	89.01%
OP16	2	8,700	1841	490	6369	1716	1528	1625	1500	0	73.21%
OP17	2	8,700	1841	490	6369	1780	1184	1560	1845	0	73.21%
OP18	2	8,700	1841	490	6369	1652	1652	1718	1347	0	73.21%
OP19	3	8,700	100	428	8172	1718	1635	1528	1690	1601	93.93%
OP20	3	8,700	120	428	8152	1752	1212	1528	1630	2030	93.70%
OP21	3	8,700	120	490	8090	1618	1620	1637	1690	1525	92.99%
OP22	3	8,700	251	428	8021	1700	1784	1742	1550	1245	92.20%
OP23	3	8,700	600	428	7672	1634	1750	1742	1535	1011	88.18%
OP24	3	8,700	200	256	8244	1600	1745	1622	1600	1677	94.76%
OP25	3	8,700	120	256	8324	1660	1690	1752	1652	1570	95.68%
OP26	3	8,700	120	256	8324	1708	1660	1734	1652	1570	95.68%
OP27	3	8,700	362	256	8082	1887	1540	1616	1654	1385	92.90%

Table 2: Machine – Operator proposed heuristic Utilisation for high order vs full inventory

Operator	**Shift**	**Total Time (Mins)**	**Idle Time (Mins)**	**Setup Time (Mins)**	**Total Busy Time (Mins)**	**Time on M1**	**Time on M2**	**Time on M3**	**Time on M4**	**Time on M5**	**Usage (%)**
OP1	1	8,700	87	428	8185	1637	1850	1637	1644	1417	94.08%
OP2	1	8,700	42	480	8178	1835	1635	1637	1644	1427	94.00%

OP3	1	8,700	120	428	8152	1630	1647	1602	1644	1627	93.68%
OP4	1	8,700	186	428	8086	1564	1617	1602	1644	1659	92.94%
OP5	1	8,700	87	256	8357	1758	1671	1600	1644	1684	96.06%
OP6	1	8,700	265	256	8179	1724	1635	1724	1644	1452	94.01%
OP7	1	8,700	265	428	8007	1590	1640	1602	1644	1531	92.03%
OP8	1	8,700	206	428	8066	1671	1613	1602	1644	1536	92.71%
OP9	1	8,700	265	490	7945	1858	1589	1602	1644	1252	91.32%
OP10	2	8,700	200	228	8272	1835	1647	1602	1644	1544	95.08%
OP11	2	8,700	120	180	8400	1724	1759	1602	1644	1671	96.55%
OP12	2	8,700	102	245	8353	1825	1671	1637	1644	1576	96.01%
OP13	2	8,700	152	390	8158	1724	1640	1637	1644	1513	93.77%
OP14	2	8,700	152	256	8292	1671	1635	1637	1644	1705	95.31%
OP15	2	8,700	128	228	8344	1837	1671	1602	1644	1590	95.91%
OP16	2	8,700	141	290	8269	1724	1671	1637	1644	1593	95.05%
OP17	2	8,700	184	290	8226	1724	1645	1647	1644	1566	94.55%
OP18	2	8,700	181	290	8229	1837	1671	1602	1644	1475	94.59%

OP19	3	8,700	100	328	8272	1637	1647	1850	1644	1467	94.77%
OP20	3	8,700	120	328	8252	1724	1589	1600	1644	1695	94.85%
OP21	3	8,700	120	390	8190	1590	1617	1637	1644	1702	94.14%
OP22	3	8,700	151	382	8167	1758	1634	1637	1644	1494	93.87%
OP23	3	8,700	100	248	8352	1671	1640	1647	1644	1804	96.62%
OP24	3	8,700	150	325	8225	1835	1589	1600	1644	1557	94.54%
OP25	3	8,700	120	225	8355	1724	1617	1600	1644	1770	96.03%
OP26	3	8,700	120	159	8421	1671	1759	1724	1644	1623	96.79%
OP27	3	8,700	132	261	8307	1724	1589	1602	1644	1748	95.48%

Table 3: Machine – Operator "As-Is" Utilisation for average order vs full inventory

Operator	Shift	Total Time (Mins)	Idle Time (Mins)	Setup Time (Mins)	Total Busy Time (Mins)	M1	M2	M3	M4	M5	Usage (%)
OP1	1	8,700	380	480	7,840	1568	1645	1562	1624	1441	90.11%
OP2	1	8,700	451	480	7,769	1553	1564	1624	1642	1386	89.30%
OP3	1	8,700	324	428	7,948	1589	1645	1624	1559	1531	91.36%
OP4	1	8,700	562	428	7,710	1560	1642	1554	1671	1283	88.62%
OP5	1	8,700	825	256	7,619	1520	1654	1640	1600	1205	87.57%
OP6	1	8,700	825	256	7,619	1448	1651	1635	1110	1775	87.57%
OP7	1	8,700	2325	428	5,947	1298	1425	1005	850	1369	68.36%
OP8	1	8,700	2345	428	5,927	1185	1196	1200	1002	1344	68.13%
OP9	1	8,700	2354	490	5,856	1171	1005	1005	850	1825	67.31%
OP10	2	8,700	380	428	7,892	1500	1647	1680	1425	1640	90.71%
OP11	2	8,700	551	480	7,669	1533	1654	1457	1215	1810	88.15%
OP12	2	8,700	563	428	7,709	1645	1635	1520	1305	1604	88.61%
OP13	2	8,700	741	425	7,534	1749	1654	1200	1425	1506	86.60%
OP14	2	8,700	1212	256	7,232	1540	1568	1600	1440	1084	83.13%
OP15	2	8,700	685	428	7,587	1517	1645	1500	1600	1425	87.21%
OP16	2	8,700	2108	490	6,102	1220	1325	1200	1005	1352	70.14%
OP17	2	8,700	2214	490	5,996	1299	1005	1200	1199	1293	68.92%
OP18	2	8,700	2651	490	5,559	1100	1200	1005	1245	1009	63.90%

Table 4: Machine – Operator proposed heuristic Utilisation for average order vs full inventory.

Operator	Shift	Total Time (Mins)	Idle Time (Mins)	Setup Time (Mins)	Total Busy Time (Mins)	M1	M2	M3	M4	M5	Usage (%)
OP1	1	8,700	384	428	7,888	1548	1524	1600	1452	1,764	90.67%
OP2	1	8,700	429	480	7,791	1624	1440	1542	1454	1,731	89.55%
OP3	1	8,700	420	428	7,852	1720	1210	1425	1608	1,889	90.25%
OP4	1	8,700	350	428	7,922	1542	1420	1200	1600	2,160	91.06%
OP5	1	8,700	380	256	8,064	1680	1540	1625	1740	1,479	92.69%
OP6	1	8,700	256	256	8,188	1540	1620	1620	1450	1,958	94.11%
OP7	1	8,700	482	428	7,790	1475	1452	1844	1002	2,017	89.54%
OP8	1	8,700	448	428	7,824	1548	1540	1600	1414	1,722	89.93%
OP9	1	8,700	521	490	7,689	1680	1440	1542	1445	1,582	88.38%
OP10	2	8,700	252	428	8,020	1520	1624	1452	1452	1,972	92.18%
OP11	2	8,700	384	480	7,836	1540	1420	1210	1680	1,986	90.07%
OP12	2	8,700	380	428	7,892	1720	1440	1542	1608	1,582	90.71%
OP13	2	8,700	448	490	7,762	1540	1620	1600	1454	1,548	89.22%
OP14	2	8,700	254	256	8,190	1548	1680	1400	1405	2,157	94.14%
OP15	2	8,700	521	428	7,751	1682	1500	1458	1608	1,503	89.09%
OP16	2	8,700	1210	490	7,000	1475	1540	1420	1542	1,023	80.46%
OP17	2	8,700	1120	490	7,090	1720	1210	1542	1454	1,164	81.49%
OP18	2	8,700	1542	490	6,668	1680	1440	1540	1540	468	76.64%

Table 5: Machine – Operator "As-Is" Utilisation for low order vs full inventory

Operator	**Shift**	**Total Time (Mins)**	**Idle Time (Mins)**	**Setup Time (Mins)**	**Total Busy Time (Mins)**	**M1**	**M2**	**M3**	**M4**	**M5**	**Usage (%)**
OP1	1	8,700	1421	580	6,699	1517	1645	1500	1600	1425	77.00%
OP2	1	8,700	1222	524	6,954	1220	1325	1200	1005	1352	79.93%
OP3	1	8,700	1005	428	7,267	1299	1005	1200	1199	1293	83.53%
OP4	1	8,700	980	690	7,030	1298	1425	1005	850	1369	80.80%
OP5	1	8,700	1254	256	7,190	1185	1196	1200	1002	1344	82.64%
OP6	1	8,700	1251	256	7,193	1171	1005	1005	850	1825	82.68%
OP7	1	8,700	2325	428	5,947	1517	1645	1500	1600	1425	68.36%
OP8	1	8,700	2345	428	5,927	1185	1196	1200	1002	1344	68.13%
OP9	1	8,700	2354	490	5,856	1171	1005	1005	850	1825	67.31%

Table 6: Machine – Operator proposed heuristic Utilisation for low order vs full inventory

Operator	Shift	Total Time (Mins)	Idle Time (Mins)	Setup Time (Mins)	Total Busy Time (Mins)	M1	M2	M3	M4	M5	Usage (%)
OP1	1	8,700	700	688	7,312	1520	1624	1452	1452	1,264	84.05%
OP2	1	8,700	1005	752	6,943	1540	1420	1210	1680	1,093	79.80%
OP3	1	8,700	995	400	7,305	1720	1440	1542	1608	995	83.97%
OP4	1	8,700	654	428	7,618	1540	1620	1600	1454	1,540	87.56%
OP5	1	8,700	654	256	7,790	1548	1680	1542	1405	1,615	89.54%
OP6	1	8,700	700	256	7,744	1682	1500	1458	1608	1,496	89.01%
OP7	1	8,700	781	428	7,491	1475	1540	1420	1542	1,514	86.10%
OP8	1	8,700	850	428	7,422	1720	1210	1542	1454	1,496	85.31%
OP9	1	8,700	699	490	7,511	1680	1440	1540	1540	1,311	86.33%

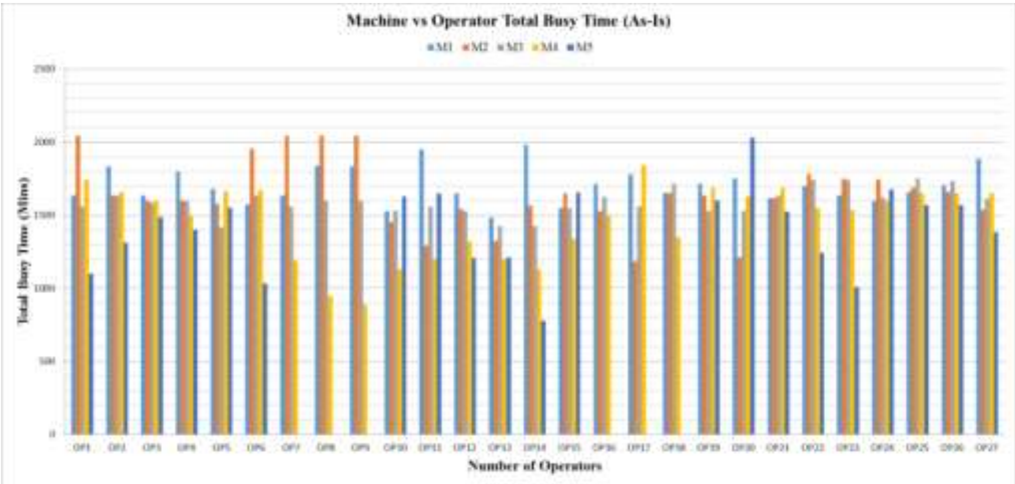


Figure 1: Machine vs operator total busy time ("As-Is") for high order full inventory scenario

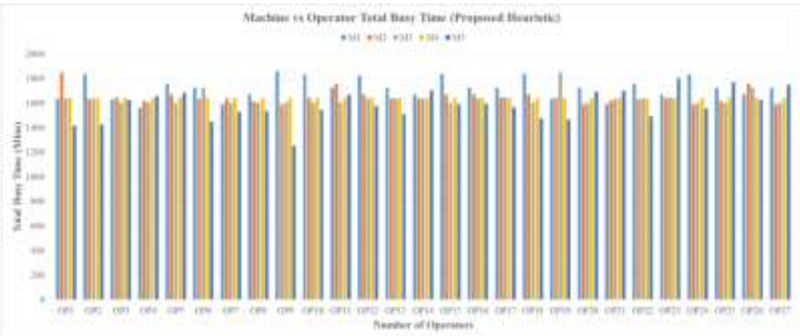


Figure 2: Machine vs operator total busy time (Proposed heuristic) for high order full inventory scenario

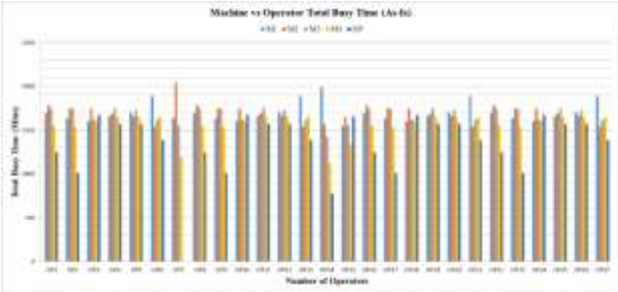


Figure 3: Machine vs operator total busy time ("As-Is") for high order safe inventory scenario

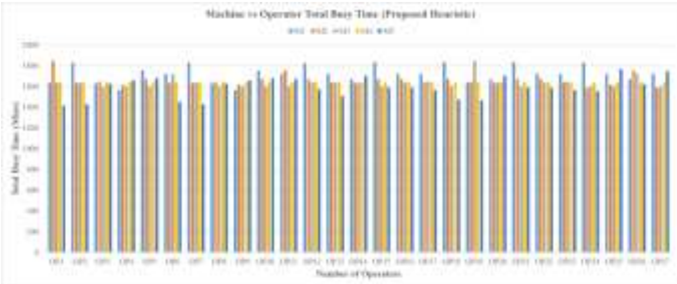


Figure 4: Machine vs operator total busy time (Proposed heuristic) for high order safe inventory scenario

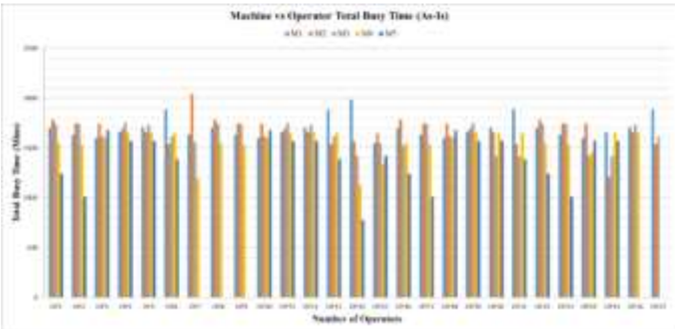


Figure 5: Machine vs operator total busy time ("As-Is") for high order critical inventory scenario

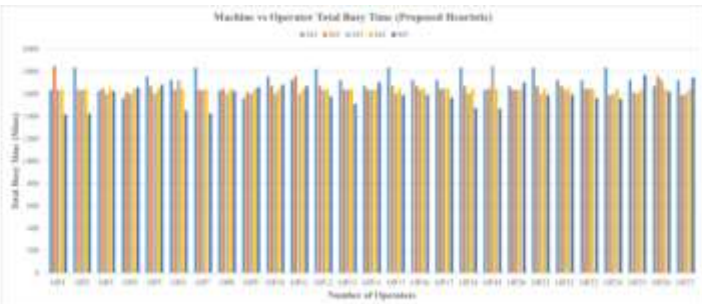


Figure 6: Machine vs operator total busy time (Proposed heuristic) for high order critical inventory scenario

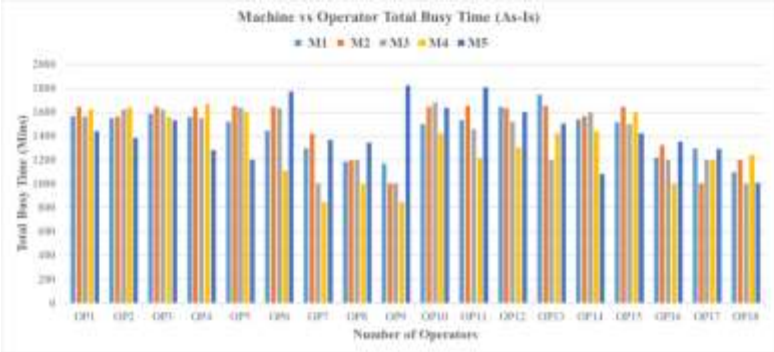


Figure 7: Machine vs operator total busy time ("As-Is") for average order full inventory scenario

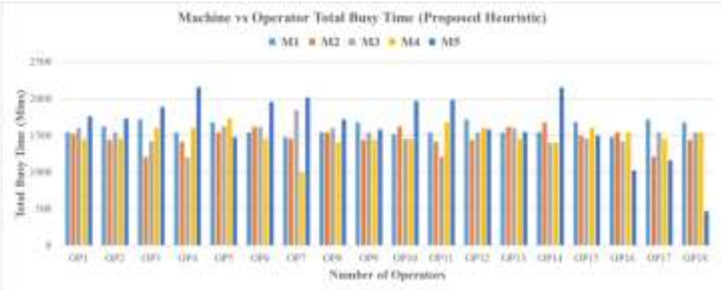


Figure 8: Machine vs operator total busy time (Proposed heuristic) for average order full inventory scenario

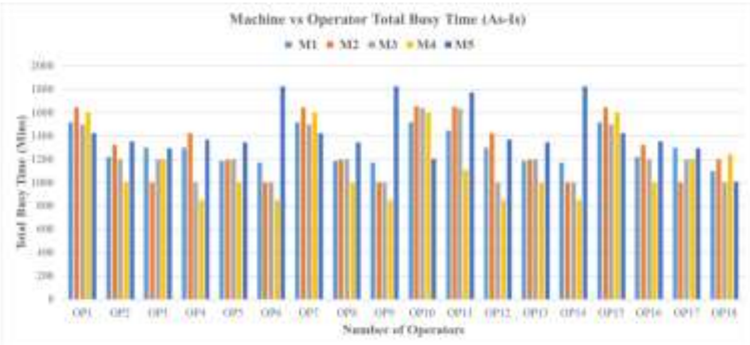


Figure 9: Machine vs operator total busy time ("As-Is") for average order safe inventory scenario

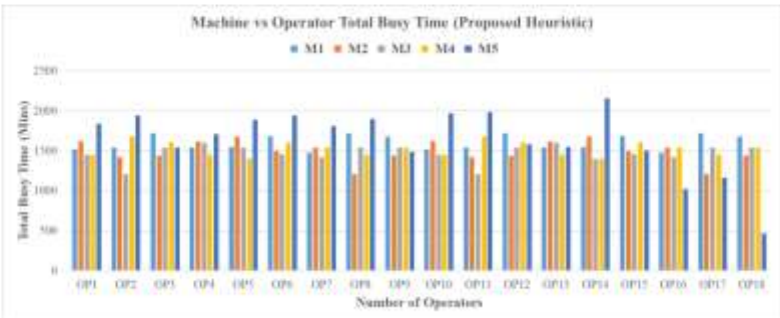


Figure 10: Machine vs operator total busy time (Proposed heuristic) for average order safe inventory scenario

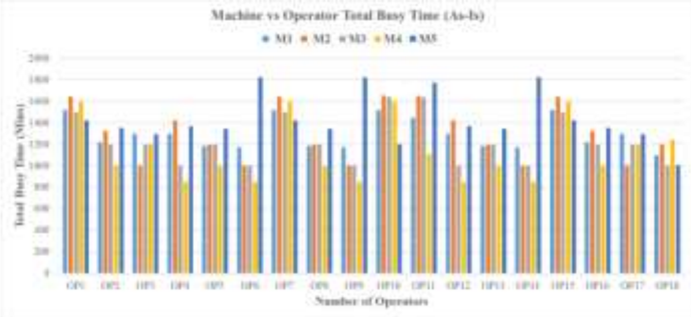


Figure 11: Machine vs operator total busy time ("As-Is") for average order critical inventory scenario

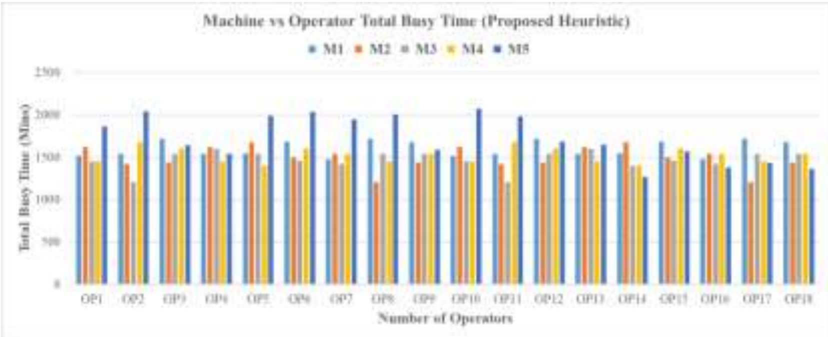


Figure 12: Machine vs operator total busy time (Proposed heuristic) for average order critical inventory scenario

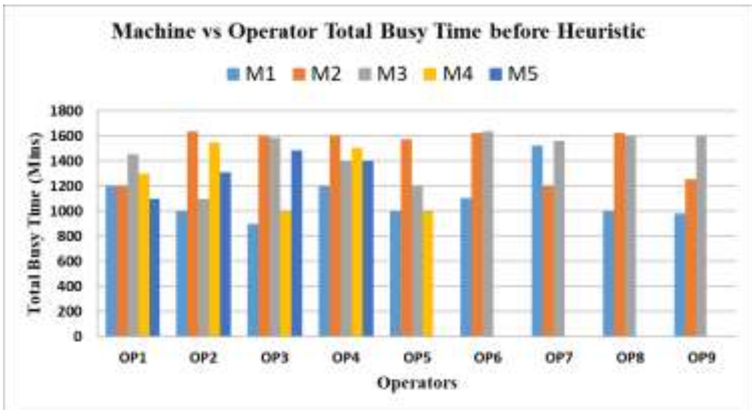


Figure 13: Machine vs operator total busy time ("As-Is") for low order full inventory scenario

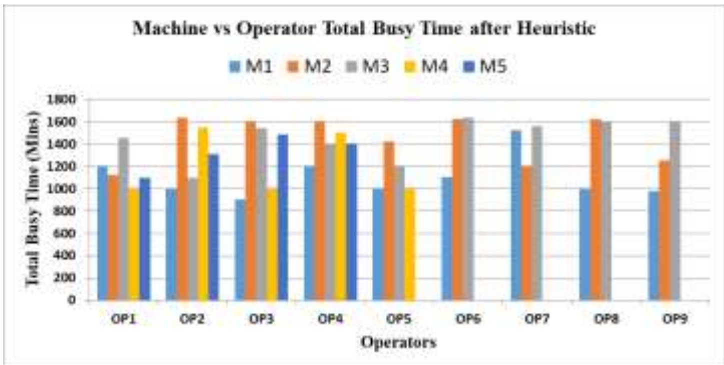


Figure 14: Machine vs operator total busy time (Proposed heuristic) for low order full inventory scenario

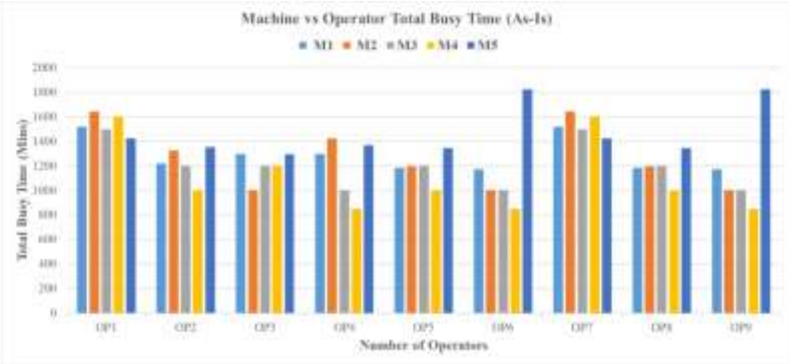


Figure 15: Machine vs operator total busy time ("As-Is") for low order safe inventory scenario

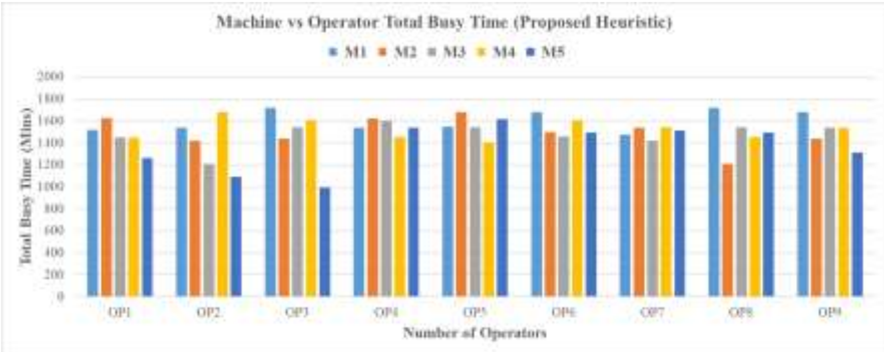


Figure 16: Machine vs operator total busy time (Proposed heuristic) for low order safe inventory scenario

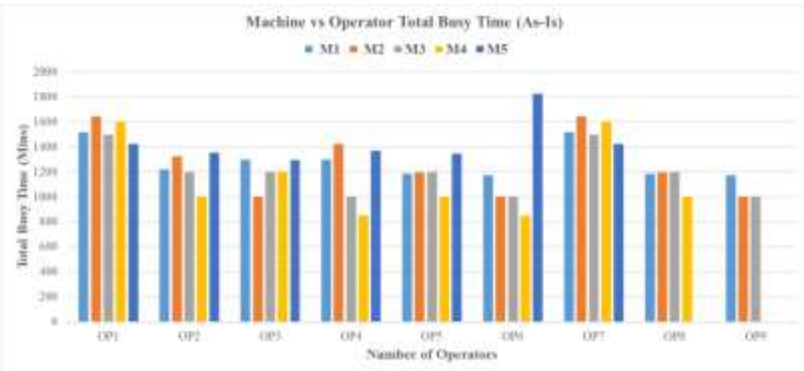


Figure 17: Machine vs operator total busy time ("As-Is") for low order critical inventory scenario

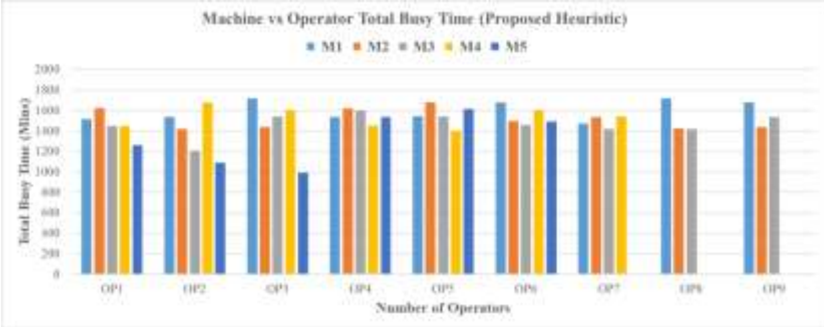
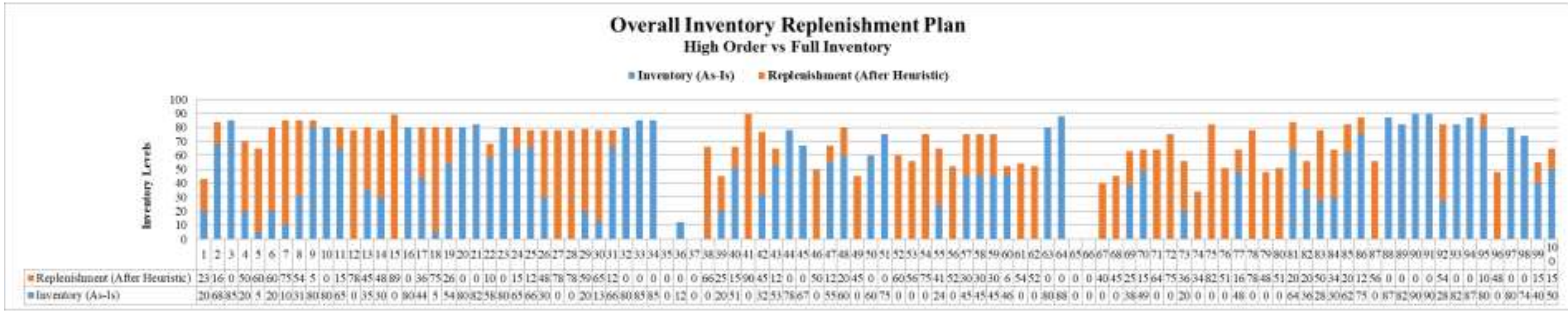
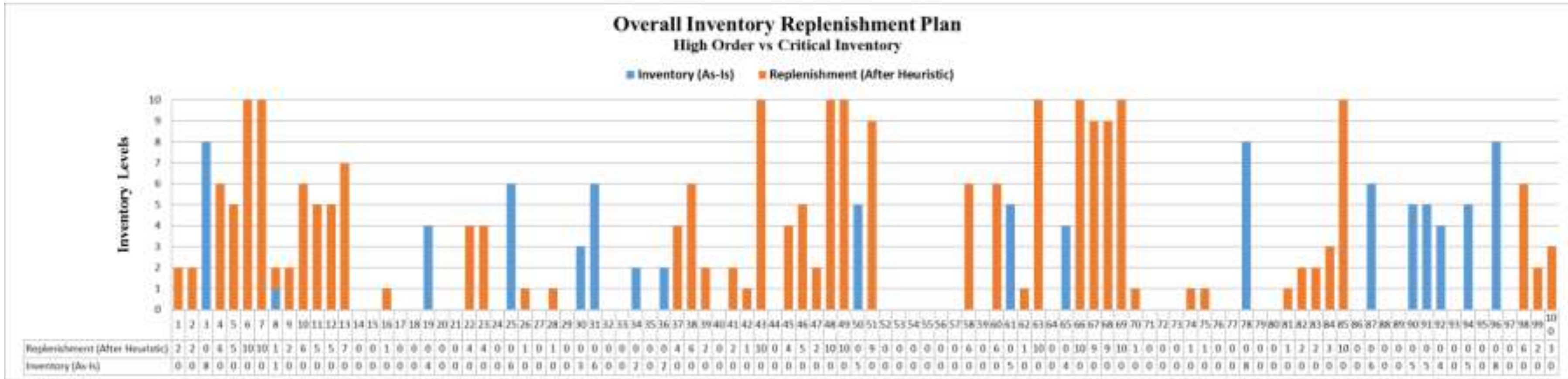
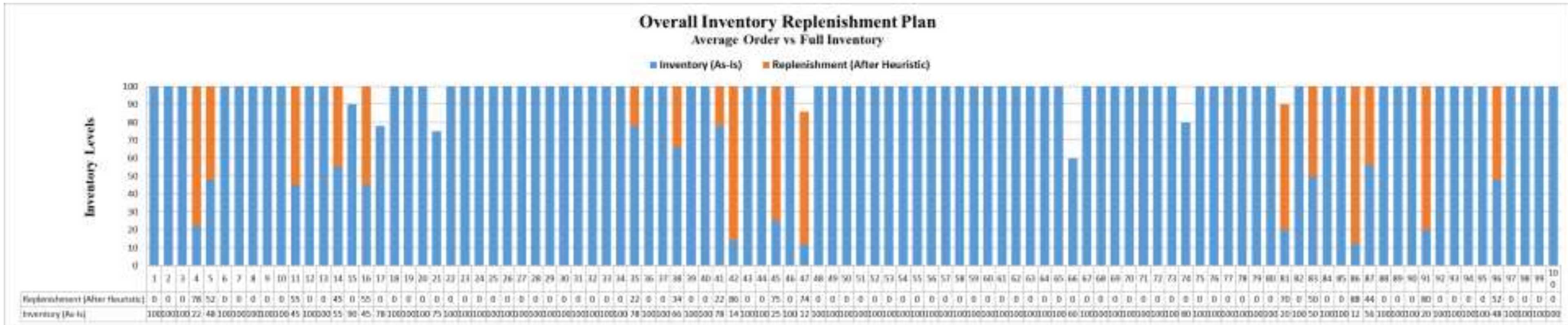


Figure 18: Machine vs operator total busy time (Proposed heuristic) for low order critical inventory scenario

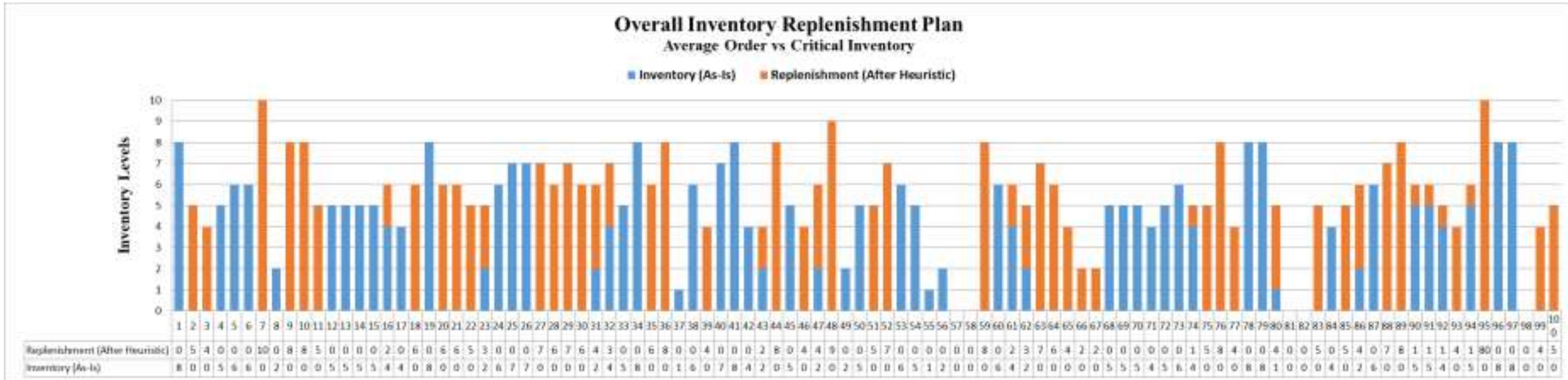
Overall Inventory Replenishment Plans for all Scenarios



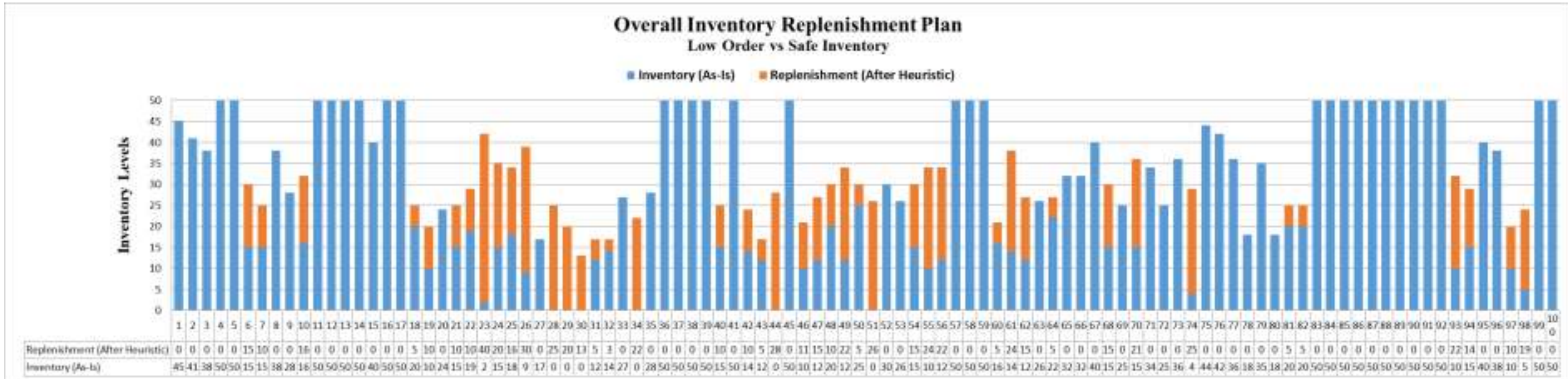

Overall Inventory Replenishment Plan
High Order vs Critical Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels
Replenishment (After Heuristic)
Inventory (As-Is)

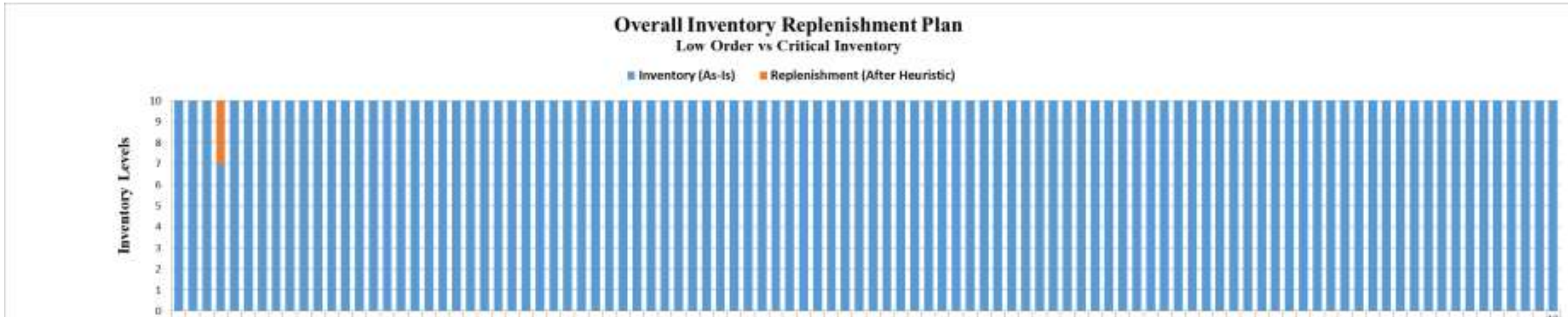

Overall Inventory Replenishment Plan
Average Order vs Full Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels
Replenishment (After Heuristic)
Inventory (As-Is)


Overall Inventory Replenishment Plan
Average order vs Safe Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels
Replenishment (After Heuristic)
Inventory (As-Is)


Overall Inventory Replenishment Plan
Average Order vs Critical Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels
Replenishment (After Heuristic)
Inventory (As-Is)


Overall Inventory Replenishment Plan
Low Order vs Full Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels


Overall Inventory Replenishment Plan
Low Order vs Safe Inventory
Inventory (As-Is)
Replenishment (After Heuristic)
Inventory Levels



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Replenishment (After Heuristic)	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory (As-Is)	10	10	10	7	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
Replenishment (After Heuristic)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory (As-Is)	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
Replenishment (After Heuristic)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory (As-Is)	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
Replenishment (After Heuristic)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Inventory (As-Is)	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

Order Disruptions Tables for all Scenarios

High Order vs Full Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
15	Cancellation	+1305	1488 of 1772	Available time
21	Due time change	-180	-	Borrow
22	Cancellation & Sequence change	+1124	1571 of 1797	Available time
27	All disruptions	+1228 -540(+688)	1633 of 1782	Available time & Borrow
62	Cancellation	+1655	1221 of 1800	Available time
64	Cancellation & Sequence change	+1150	1345 of 1624	Available time
65	Cancellation & Due time Change	+1110 -240 (+870)	1116 of 1799	Available time/Borrow
66	All Disruptions	+1254 -240(+1014)	1250 of 1710	Available time/ Borrow
69	Cancellation	+1018	1505 of 1785	Available time
70	Cancellation	+1254	1226 of 1790	Available time
74	Cancellation & Due date change	+1336-180 (+1156)	1260 of 1782	Available time/ Borrow
75	Cancellation & Due date change	+1219-180 (+1069)	925 of 1791	Available time/Borrow
81	Cancellation & Sequence change	+1260	1230 of 1794	Available time

89	All Disruptions	+1256-180 (+1076)	1255 of 1784	Available time/ Borrow
99	All Disruptions	+1030-480(+550)	1160 of 1782	Available time/Borrow
100	Cancellation	+1140	1220 of 1792	Available time

High Order vs Safe Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
3	Cancellation	+1115	1205 of 1780	Available time
5	Cancellation	+1220	1210 of 1700	Available time
6	Cancellation	+924	1040 of 1780	Available time
10	All Disruptions	+1245-240(+1005)	985 of 1756	Available time & Borrow
24	Due time change	-560	-	Borrow
55	All Disruptions	+964-240(+724)	1208 of 1788	Available time & borrow
60	Cancellation	+1125	958 of 1721	Available time
65	All Disruptions	+1245-1002(+243)	1345 of 1778	Available time & Borrow
78	Sequence and Due date change	-560	-	Borrow

89	All disruption	+1124-560(+564)	1110 of 1784	Available time & Borrow

High Order vs Critical Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
1	All Disruptions	+1124-240(+884)	1248 of 1754	Available time & Borrow
2	All Disruptions	+1248-240(+1008)	1261 of 1785	Available time & Borrow
12	Cancellation	+1248	900 of 17400	Available time
15	Sequence and Due date change	-240	-	Borrow
16	Sequence and Due date change	+560-300(+260)	-	Available time & Borrow
17	Cancellation & Sequence change	+858	1210 of 1784	Available time & Borrow
24	All Disruptions	+1005-300(+705)	1245 of 1744	Available time & Borrow
26	Cancellation	+900	1200 of 1754	Available time
41	Cancellation & Due date change	+1142-300(+842)	1348 of 1785	Available time & Borrow
56	Cancellation	+788	1225 of 1770	Available time
59	Cancellation & Due date change	+1268-420(+848)	1250 of 1750	Available time & Borrow
60	Cancellation & Sequence change	+1240	1120 of 1774	Available time
75	All Disruptions	+1200-300(+900)	850 of 1725	Available time & Borrow

84	All Disruptions	+1124-300(+824)	995 of 1745	Available time & Borrow
89	Cancellation & Due date change	+905-240(+665)	1241 of 1780	Available time & Borrow
90	Cancellation	+217	1452 of 1710	Available time
91	Cancellation & Due date change	+448-360(+88)	1348 of 1749	Available time & Borrow
92	All Disruptions	+1248-240(+1008)	1245 of 1741	Available time & Borrow
99	Sequence and Due date change	-300	-	Available time & Borrow

Average Order vs Full Inventory

Order No	**Disruption Type**	**Time consequences (Mins)**	**Quantity Consequences (Units)**	**Impact on Production**
5	Cancellation	+914	748 of 794	Available time
18	All Disruptions	+840-120(+720)	714 of 778	Available time & Borrow
22	Sequence and Due date change	-240	-	Available time & Borrow
23	Sequence and Due date change	-240	-	Borrow
30	All Disruptions	+780-240(+540)	650 of 854	Available time & Borrow
45	All Disruptions	+958-240(+718)	745 of 795	Available time & Borrow
47	Cancellation & Sequence change	+480	740 of 889	Available time
52	Cancellation	+745	658 of 740	Available time

68	Cancellation & Due date change	+240-240(0)	710 of 874	Available time & Borrow
74	Sequence and Due date change	-120	-	Borrow
78	Cancellation	+685	542 of 784	Available time
88	All Disruptions	+745-240(+505)	662 of 890	Available time & Borrow
90	Cancellation & Due date change	740-240(+500)	545 of 904	Available time & Borrow

Average Order vs Safe Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
1	Cancellation & Due date change	+700-560(+140)	520 of 784	Available time & Borrow
2	Cancellation	+560	648 of 854	Available time
3	Cancellation & Sequence change	+124	620 of 745	Available time
4	All Disruptions	+540-240(+300)	640 of 700	Available time & Borrow
10	All Disruptions	+648-120(+528)	784 of 889	Available time & Borrow
15	Sequence and Due date change	-240	-	Borrow
16	Cancellation	+995	784 of 784	Available time
24	Cancellation & Sequence change	+450	685 of 873	Available time
25	Sequence and Due date change	-300	-	Available time & Borrow
26	Cancellation & Due date change	+542-120(+422)	620 of 887	Available time & Borrow

31	All Disruptions	+584-120(+428)	650 of 870	Available time & Borrow
35	All Disruptions	+684-120(+564)	455 of 802	Available time & Borrow
36	Cancellation & Due date change	+620-120(+500)	660 of 780	Available time & Borrow
41	Cancellation & Due date change	+528-240(+288)	654 of 785	Available time & Borrow
46	Cancellation	+621	640 of 712	Available time
47	Cancellation & Due date change	+484-120(+364)	600 of 750	Available time & Borrow
55	All Disruptions	+525-120(+405)	721 of 786	Available time & Borrow
60	Cancellation	+584	750 of 845	Available time
64	Sequence and Due date change	-420	-	Borrow
67	Sequence and Due date change	-420	-	Borrow
68	All Disruptions	+574-420(+154)	741 of 802	Available time & Borrow
69	Cancellation	+440	699 of 785	Available time
70	All Disruptions	+580-420(+160)	654 of 784	Available time & Borrow
74	Cancellation & Due date change	+541-120(+421)	450 of 740	Available time & Borrow
76	Sequence and Due date change	-420	-	Available time & Borrow
77	All Disruptions	+562-420(+142)	487 of 780	Available time & Borrow
82	Cancellation & Sequence change	+540	520 of 745	Available time & Borrow
98	All Disruptions	+480-120(+360)	500 of 789	Available time & Borrow

100	Sequence and Due date change	-560	-	Borrow

Average Order vs Critical Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
4	Sequence and Due date change	-560	-	Borrow
6	Cancellation	+562-120(+442)	451 of 750	Available time
10	All Disruptions	+541-240(+301)	520 of 748	Available time & Borrow
11	Sequence and Due date change	-240	-	Available time & Borrow
12	Cancellation & Due date change	+520-240(+280)	480 of 712	Available time & Borrow
16	Sequence and Due date change	-240	-	Borrow
19	Sequence and Due date change	-120	-	Borrow
38	Cancellation & Due date change	+540-120(+420)	523 of 740	Available time & Borrow
55	Cancellation & Sequence change	+560	621 of 784	Available time
64	Due date change	-120	-	Borrow
75	Sequence and Due date change	-120	-	Borrow
95	Due date change	-420	-	Borrow
99	Sequence and Due date change	-120	-	Borrow
100	Cancellation	+485-120(+365)	710 of 785	Available time

Low Order vs Full Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
4	All Disruptions	+240-240(0)	366 of 450	Available time & Borrow
5	Sequence and Due date change	0	-	Borrow
12	Cancellation	+227	435 of 450	Available time
23	All Disruptions	+560-240(+320)	402 of 458	Available time & Borrow
45	All Disruptions	+560-120(+440)	420 of 457	Available time & Borrow
65	All Disruptions	+240-120(+120)	402 of 510	Available time & Borrow
79	Cancellation & Due date change	+562-120(+442)	425 of 574	Available time & Borrow
80	All Disruptions	+562-120(+442)	470 of 598	Available time & Borrow
84	Sequence and Due date change	0	-	Borrow

Low Order vs safe Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
16	Cancellation & Due date change	+562-240(+322)	425 of 500	Available time & Borrow
18	All Disruptions	+240-240(0)	420 of 487	Available time & Borrow
21	Sequence and Due date change	-300	-	Borrow

24	Cancellation	+240	442 of 489	Available time
52	All Disruptions	+560-300(+260)	425 of 438	Available time & Borrow
63	All Disruptions	+240-300(-60)	225 of 402	Available time & Borrow
66	Sequence and Due date change	0	-	Borrow
74	Cancellation	+240	254 of 457	Available time
77	Cancellation	+241	124 of 450	Available time
85	All Disruptions	+480-300(+180)	345 of 448	Available time & Borrow
87	Cancellation & Sequence change	+480	358 of 420	Available time
92	Cancellation & Due date change	+480-300(+180)	425 of 459	Available time & Borrow

Low Order vs Critical Inventory

Order No	Disruption Type	Time consequences (Mins)	Quantity Consequences (Units)	Impact on Production
12	Cancellation	+480	420 of 450	Available time
13	Sequence and Due date change	-120	-	Borrow
36	Sequence and Due date change	0	-	Borrow
40	Cancellation & Sequence change	+240	356 of 459	Available time
41	Cancellation	+480	405 of 450	Available time
62	Cancellation & Due date change	+560-120 (+440)	400 of 480	Available time & Borrow

64	Cancellation & Due date change	+560-120(+440)	420 of 487	Available time & Borrow
78	All Disruptions	+480-120(+360)	129 of 408	Available time & Borrow
88	All Disruptions	+480-120(+360)	120 of 448	Available time & Borrow
89	Cancellation	+480	255 of 438	Available time
91	Cancellation	+256	251 of 450	Available time